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Abstract

We examine the diffusion of more than twenty technologies across twenty-three of the world's leading industrial economies. Our evidence covers major technology classes such as textile production, steel manufacture, communications, information technology, transportation, and electricity for the period 1788-2001. We document the common patterns observed in the diffusion of this broad range of technologies.

Our results suggest a pattern of trickle-down diffusion that is remarkably robust across technologies. Most of the technologies that we consider originate in advanced economies and are adopted there first. Subsequently, they trickle down to countries that lag economically. Our panel data analysis indicates that the most important determinants of the speed at which a country adopts technologies are the country's human capital endowment, type of government, degree of openness to trade, and adoption of predecessor technologies. We also find that the overall rate of diffusion has increased markedly since World War II because of the convergence in these variables across countries.

Keywords: Economic growth, historical data, technology adoption.
JEL-codes: N10, O30, O57

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1. Introduction

More and more evidence related to cross-country economic performance suggests that there are major differences in cross-country levels of TFP. Klenow and Rodriguez-Clare (1997) show that over 60 percent of income per capita differences in 1985 cannot be explained by differences in physical or human capital. Caselli and Coleman (2000) show that TFP differences between poor and rich countries are even larger once we allow for the existence of appropriate technologies. Jerzmanowski (2002) shows that the bulk of cross-country TFP differences are due to the inefficient use or delayed adoption of new technologies by trailing countries. It is therefore important to understand the factors that generate the observed cross-country differences in the technology used.

There is a long theoretical literature that has tried to understand why firms implement non-state of the art technologies. In section 4 we review these different explanations in detail. On the empirical side, economic historians have illustrated numerous cases where each of these theories is important. These case studies typically involve one or two technologies and a couple of countries. Caselli and Coleman (2000) have recently extended this approach to the OECD countries in order to study the determinants of computer adoption in the last thirty years.

The problem with these analyses is that they do not provide us with the big picture. Because they consider specific countries or specific technologies, it is hard to distinguish technology specific or country specific anecdotes from general adoption patterns. Since most of economic theory tends to aim for explaining general facts rather than specific anecdotes, it is worthwhile to distill out the adoption and diffusion processes that most major technologies seem to have in common.

In this paper we document these general cross-country technology adoption patterns using a new historical data set for the World's leading industrialized economies. Specifically, we consider 25 major technologies in 23 countries over a period that spans for over 200 years. Essentially, we apply a cross-country growth methodology approach to technology adoption, rather than to per capita income, TFP, or imports.

Focusing on explaining the adoption of specific technologies has three clear advantages over using proxies like TFP, as in Coe and Helpman (1995), or the value of imports by sector at a more or less disaggregate level, as in Caselli and Wilson (2002). First, by using a more disaggregate measure of technology we reduce the risk of having heterogeneity in the measures of technology, say across countries or over time. Second, by having data on various specific technologies we explore the existence of interactions across the adoption of the different technologies. Finally, by having a 'micro' measure of technology as the dependent variable, we are inclined to interpret the identified correlations with aggregate explanatory variables as 'causal' relations.

Our analysis in this paper consists of four distinct steps. In the first we introduce our data set and describe the value added of considering data that provide evidence for different technologies, countries, and years. In the second step we provide a set of descriptive statistics that illustrate the validity of the data set and help us to document the main characteristics of the cross-country technology adoption processes for the technologies that we consider. The third step consists of a brief review of existing theories on cross-country technology adoption and their predictions. These predictions are then compared to the facts unearthed in the second step. Finally, we present evidence from panel data regressions that helps us to assess which are the major determinants of the observed cross-country disparities in technology adoption rates.

What emerges from our analysis in the second step is a picture of trickle down diffusion that is very robust across technologies. The rich technological leaders tend to be the ones that innovate and that adopt new technologies the earliest. After the initial adoption by the leading countries, the laggards follow suit and partially catch up with the leaders. The rate at which the followers are catching up with the leaders has increased since WWII. These simple observations are at odds with the predictions of some of the most commonly used theoretical models on technology adoption, like the vintage capital models of Solow (1960) and Gilchrist and Williams (2001).

Our fourth step addresses the determinants of the rate at which these technologies trickle down. In line with previous research, by for example Caselli and Coleman (2001) and Lee (2000), we observe that income per capita, human capital and openness have a positive effect on the level of technology adoption. In terms of political institutions, countries where the effective executive power is in hands of the military or of an agent that does not hold any public position tend to adopt technologies more sluggishly. Another deterrent of the adoption of technologies is having an effective legislative power. We also find that there are important interactions between technologies. For example both the level of the preceding technology and the production of electricity have a positive effect on the degree of adoption of the current technology.

The effects of these determinants turn out to vary substantially across technologies and over time. For example, human capital, trade openness and the effectiveness of the legislature are more important in the post-War period than before, while the type of regime and the type of executive seem to matter more for the pre-1945 period. Our results lead us to conjecture that the acceleration in the technology catch up process observed since WWII is associated with the convergence of the main determinants of technology adoption like openness, human capital or the type of regime across the sample of countries that we consider. On the one hand, this is due to a convergence in the endowments across countries that determine the efficient adoption of technologies. On the other hand, this reflects the joint abolishment across the countries in our sample of various barriers that impeded the efficient adoption of technologies.

The rest of the paper is structured as follows. In Section 2 we take our first step and describe our data set. Section 3 contains evidence on general patterns regarding the adoption of the different technologies, the existence of lock in, whether there is leapfrogging, and the evolution of the speed of diffusion of technologies. Section 4 describes the proposed theories of the determinants of cross-country variation in technology adoption emphasizing whether they fit these patterns or not and our identification strategy. Section 5 contains the regression analysis and section 6 concludes.

2. A cross-country dataset of technology adoption

At the heart of the empirical analysis in this paper is the Historical Cross-Country Technology Adoption Dataset (HCCTAD) that we introduced in Comin and Hobijn (2003). This dataset contains historical data on the adoption of many technologies over the last 215 years for 23 of the World's leading industrial economies. This section contains a description of what the use of the HCCTAD adds to other empirical evidence.

From the HCCTAD, we use data that cover the adoption of 25 major technologies over the last two centuries. Table 1 lists the sample period, countries, as well as the technologies included in the analysis in this paper.

The countries that are included in our data set basically coincide with the sample of advanced economies for which Madisson (1995) collected data on real GDP per capita. It is a slightly bigger sample of countries than Madisson's core-sample used by Baumol (1986) and Bernard and Durlauf (1995). The main reason that we limit ourselves to this sample of countries is simply that these are the countries for which most data are available[1].

The technologies in our sample have been classified by us into eight groups that cover (*i*) textiles production technologies, (*ii*) steel production technologies, (*iii*) telecommunication, (*iv*) mass communication, (*v*) information technology, (*vi*) transportation (rail-, road-, and airways), (*vii*) transportation (shipping), and (*viii*) electricity. Table 1 lists the technologies in each group sequentially, in the sense that the earliest technologies are listed first. There is one exception. That is, for information technology there is no such historical sequence between industrial robots and PC's.

As can be seen from Table 1, we use six different proxies for the level of technology adoption. The first, applied for the data on steel technologies, measures *shares of output* produced using various production technologies. The second, used for textiles and shipping, measures *capital shares* rather than output shares. It measures the fraction of a capital stock that is made up of equipment that embodies a particular technology. Thirdly, for other technologies that are predominantly used in production, like trucks and robots, we measure *capital output ratios*. That is, we use the amount of equipment of a particular technology as a ratio of real GDP. For some production technologies we do not have capital stock data but only data on output produced, like ton-kilometers (TKM) of freight transported using various transportation methods. For those technologies we use *production to real GDP ratios*. Our final two measures normalize capital stocks and consumption by the population rather than real GDP. *Capital stocks per capita* are used for example for passenger cars per capita and mobile phones per capita. *Consumption per capita* is used for mail, telegrams, as well as passenger transportation variables.

In spite of the different ways we measure technology adoption for the technologies in our sample, these measures have one important thing in common. All of them are a proxy of the intensity with which a technology is used in a particular economy.

The degree of heterogeneity among the technologies that we consider is both a vice and a virtue. It is a vice because it leads to many technology specific issues possibly affecting our analysis and conclusion. On the other hand, this heterogeneity it is a virtue because the facts that we find to be common among many technologies can be considered general properties of the underlying adoption processes that are worth capturing in a general theory of technology diffusion. In this sense we extend a previous literature that has explored the determinants of technology adoption. Previous studies tend to focus either on more than one

[1] By limiting our sample to the ex-post successful countries are results are thus conditional on being one of the World's industrial leaders. This point was made by De Long (1988) in response to Baumol (1986) and is important to bear in mind when interpreting the evidence that we present in what follows.

technology for one country, as in Harley (1973), or on one particular technology for two or more countries, as in Pollard (1957), Lee (2000), Saxonhouse and Wright (2000), and Caselli and Coleman (2001).

The HCCTAD allows us to conduct independent analyses for different technology clusters or time periods to try to illustrate technological idiosyncrasies. Conditioning on a particular technology, we essentially have a standard cross-country panel data set. That is, for each technology we have information about variation in adoption across both countries and time. Because we will use these two dimensions of variation intensively in the first empirical part of this paper, it is useful to consider them in detail. Table 2 contains a representation of these two dimensions. Along the cross-sectional dimension we will distinguish between technologies that were adopted quicker by the rich countries than by the (relatively) poor countries and ones for which the opposite was true. Along the time-dimension we differentiate between technologies that took a (relatively) long time to be adopted after their invention and ones that were adopted quickly.

The reason that we focus on these two dimensions is that they yield essentially four classes of models, each corresponding to each of the cells. Similarly, it turns out that a relatively simple descriptive statistical analysis allows us to categorize the observed technologies into these four cells. Hence, combining these two dimensions yields a match between the theoretical predictions of some of the models on technology adoption and the empirical evidence collected in the paper.

In the next section we present a series of descriptive statistics taken from the HCCTAD for all technologies.

3. Descriptive statistics

Before we dive into the details of the data set, we will first present some general facts that we distill from it. The facts presented in this section serve two distinct purposes. First of all, these statistics illustrate the overall validity and reasonability of the HCCTAD. Most importantly, the basic facts presented here allow us to show the overall patterns that are common across technologies as well as help us to partially classify technologies in the cells of Table 2.

Our descriptive analysis in this section consists of three parts. In the first part we present the sample sizes of the cross sections available for each technology at several points in time as well as the means, coefficients of variation, and speeds of convergence. This part is meant to underline the breadth and depth of the coverage of the technologies in the data set and to give a broad outline of the development of these technologies over time. In the second part we consider the correlation between the adoption rates of the various technologies and a country's per capita GDP level. This part will allow us to tentatively categorize the technologies in the two columns of Table 2. Finally, we use more anecdotal evidence for a limited set of technologies to distinguish between the rows of Table 2 in the third part of this section.

Sample size, mean, and coefficient of variation

Table 3 lists the cross sectional mean of the technology measures that we consider as well as the size of the cross-section at eight points in time during the period 1880 through 1990. We have cut this period in intervals of 20 years each and additionally report data for 1970 and 1990. Because of WWII, the table contains results for 1938 instead of 1940. The second column in the table reports to which technology measure in Table 1 each row corresponds. The first line of the table contains real GDP per capita in 1998 US$.

The most important observation to take away from this table is that the data cover the bulk of our sample of countries, even for the technologies for which we have data in the early part of the sample period. Data for mail, telegrams, phones, rail transportation, and merchant shipping is available for the turn of the Twentieth Century for more than ten countries. Furthermore, after 1960 we have at our disposal cross sections of size 15 or larger for each of our technologies, except textile production and merchant shipping. The latter two are of less interest during that period, because virtually all countries in our sample had fully adopted ring spindles and steam/motor ships at that time anyway.

A caveat that can be observed from the sample sizes is that our data do not contain much information about the diffusion of the technology during its early introductory[2] phase. In order to see this, consider the examples of phones and cars. The telephone was invented by Alexander Graham Bell in 1876. However, it took most countries until 1900 to publish official statistics on the extent of their phone networks. Hence, the data only give scattered evidence on the first twenty years of the cross-country diffusion of telephones. A similar delay can be seen for cars. In 1885 Gottlieb Daimler built the first combustion engine powered vehicle. However, fifteen years later data on the number of passenger cars owned are only available for France and the U.S.. Hence, official statistics are generally only collected for products and technologies that turn out to be important. A technology's importance can only be determined after its introductory period. This selection effect therefore implies that data do not tend to cover the introductory phase.

Finally, Table 3 also illustrates that we are dealing with a panel that is unbalanced in two dimensions: In terms of the sample of countries available for each particular technology as well as the sample of technologies that are available over time. Throughout the rest of this paper we will only refer to the unbalanced nature of our panel when presenting results that are particularly sensitive to the changing sample.

The average technology adoption measures are a bit harder to interpret because they are measured in different units. The spindles, steel variables, as well as the steam- and motorships variable are all measured as (capital or output) shares.

The data for the ring spindles turn out to be relatively noisy and also cover a small sample of countries. For the steel variables we find that over the available sample period, i.e. 1935-2001, Bessemer and Open Hearth Furnace steel production have been fully phased out. Blast Oxygen steel production was invented in 1950 and has since become the predominant steel production method. Electric Arc Furnaces, invented in 1900, have continuously been used for the production of more advanced steel alloys and, due to increases in their efficiency, have gained share in the 1980's and 1990's. Steam- and motorships have fully replaced sailships in the merchant fleets of the countries in our sample. However, notice that the point of full replacement occurred only in the 1960's.

All telecommunications (*III*) and mass communications (*IV*) variables are measured in units per capita. The use of all telecommunications technologies has increased over time, except for telegrams. The

[2] Following product life cycle theory, explained in for example Kotler (1986), we will distinguish four phases for technology adoption (*i*) introduction, (*ii*) growth, (*iii*) maturity, and (*iv*) decline.

introduction of the telephone has led to a steady decline of telegrams per capita. With respect to mass communication, average newspaper use per capita did not increase during the 20 years for which we have data. However, radio and television use have grown rapidly since WWII.

The use of rail-, road, and airways has intensified continuously during the Twentieth Century. The only exception is rail cargo, for which the TKM transported per unit of real GDP has declined as the use of trucks has grown. Surprisingly, average passenger kilometer on rail per person has been growing during the whole sample period.

Finally, electricity output, measured as MWHr produced per unit of real GDP, in 1990 was one hundred times higher than ninety years earlier. This reflects the widespread adoption of electricity as a general purpose technology (GPT) during the past century.

Though the average adoption measures tell us something about the trends in technology adoption for the countries in our sample, they do not give us information about the adoption disparities that are our main focus in this paper. In order to illustrate the adoption disparities we compute in Figure 2 the cross-sectional coefficients of variation.

Our interest of the coefficients of variation is twofold. First, given the positive correlation between the degree of technology adopted and GDP per capita that we document below, by comparing the cross-country dispersion in technology adopted with the dispersion in GDP per capita we can have an idea of the role of technology adoption differences in the cross-country dispersion of income levels. Second, by studying the time series evolution of the coefficient of cross-section variation of technology adoption, we can assess the convergence patterns in technology.

Figure 1 reports the cross-country coefficient of variation of average income per capita over 5 years for each interval between 1880 and 2000. The largest coefficient of variation is about 0.4. In Figures 2a and 2b we report the cross-country coefficient of variation for 22 technologies. Eyeballing is sufficient to assess that the typical cross-country dispersion in technologies is quite larger than 0.4. This implies that dispersion in technologies across industrialized countries is larger than the dispersion in income per capita levels. This finding is quite interesting because this is what is predicted by models of appropriate technologies like Basu and Weil (1998), Acemoglu and Zilibotti (2001) and Caselli and Coleman (2002).

The path of the coefficient of variation has often been considered for real GDP per capita. The observed persistent decrease in the coefficient of variation in real GDP per capita for the World's industrialized leaders was first documented by Easterlin (1960) and is known as σ-convergence. It is consistent with the predictions of the neoclassical growth model that followers will catch up with economic leaders.

We consider whether we observe similar catch up dynamics for our measures of technological adoption. In order to consider these catch up dynamics, we calculated time-varying coefficients of variation for the technology measures covered by our data set. These dynamic coefficients of variation are plotted in Figures 2a and 2b.

The coefficients of variation in this figure indicate that we observe catch up dynamics for almost all technologies that are in their innovation, growth, and maturity phases. For steel production technologies we observe declines in the coefficients of variation for BOF and EAF production. For telecommunications the coefficients of variation are decreasing for phones and cellphones. Televisions are the mass communications technology that saw the biggest decline. Even for PCs, the data for which only cover a short sample period, we can observe a pronounced catch up effect. Road- and airway transportation also saw decreases in their technology diffusion disparities. The decreases for rail transportation are less pronounced and the disparities in the intensity of rail transportation use across countries actually seem to have increased since about 1970. The schoolbook example of convergence in technologies is shipping. After initial big differences in the adoption rates of steam- and motorships, the latter have now become the sole class of ships of all merchant fleets under consideration. This is reflected in the coefficient of variation going to zero over the past 150 years. Finally, after an initial increase during the Interbellum, we also observe a decline in the disparity in electricity intensity of GDP across countries.

For technologies that have reached their decline phase the catch up effect is not observed. This is not surprising, because there is little incentive to catch up in outdated technologies. This can be observed, for example, for textile production, Bessemer and OHF steel[3], telegrams, and newspapers.

Just like for GDP, the rate of convergence in technology adoption seems to have increased in the post-WWII period. Two observations back this observation up. First of all, for technologies like telephones, cars, trucks, aviation, and electricity, we observe steeper declines in the coefficient of variation after WWII than before. Secondly, for technologies that were introduced after WWII, like BOF steel, cellphones, televisions[4], and even PCs, we see declines in the coefficient of variation that were unprecedented for pre-WWII technologies.

To make this claim more formally, we estimate the speed of convergence with the following regression:

$$Y_{ijt} = \alpha + \beta Y_{ijt-1} + e_{ijt} \tag{1}$$

In equation (1), Y_{ijt} denotes the measure of technology adoption for the j^{th} technology in country i at time t, where this measure is in logs whenever the variable is not a share. The speed of convergence is then given by $-\ln(\beta)$. Table 4 reports the estimates of β for several partitions of the sample. The estimates in the first row pools together all the time periods, while the second and third row estimates correspond, respectively, to the samples before and after 1945. The columns partition the data set by technological groups. The first column pools together all the technologies while the rest contain estimates of equation (1) for each of the eight technology groups. The first remarkable observation is that the speed of convergence implied by these estimates is quite high. The average speed is 11.4 percent. This is in line with the magnitudes obtained in the convergence literature for GDP per capita when we control for differences in the steady states with country specific fixed effects. Second, the acceleration seems quite remarkable both on average and within technology groups. On average the speed of convergence in the technologies adopted has increased from 10 to 14 percent. Further, in five of the six technological clusters for which we have some variation both before and after 1945 we observe an acceleration of the speed of convergence.[5]

[3] Part of the increase in the coefficient of variation of Bessemer and OHF steel is caused by a denominator effect. This is because the average shares of these types of steel go to zero at the end of the sample period.

[4] Even though the television was invented in 1924, its mass-production and adoption only started after WWII.

[5] The exception is electricity.

In sum, we observe large differences in the rate of adoption of technologies across the leading industrialized countries in the World. Over time, the slower adopters tend to catch up with the technological leaders. In fact, the rate at which the laggards draw near the leaders has increased considerably since 1945.

Correlations with real GDP per capita

How are the observed disparities in technology adoption related to the disparities in real GDP per capita that are more commonly studied in the empirical literature on economic growth? In order to answer this question, we consider the dynamic correlations between our technology adoption measures and the logarithm of real GDP per capita.

Klenow and Rodríquez-Clare (1997) find that the correlation between log-TFP levels and the logarithm of output per worker for 98 countries in 1985 is 0.93. This astoundingly high correlation suggests that, at the aggregate level, that there is a large interdependence between the level of technology/productivity and economic development. In terms of growth rates, Klenow and Rodríquez-Clare (1997) as well as Easterly and Levine (2001) find similarly that the cross-country correlation between TFP growth and the growth of output per worker is about 0.9.

Differences in total factor productivity can be divided into two sources. The first is differences in the level of efficiency with which countries use the same technologies. The second, and the main focus of the paper here, is the disparity in the rate at which countries adopt more advanced technologies. The dynamic correlations between our technology adoption measures and log real GDP per capita that we present in Figures 3a and 3b are meant to illustrate the importance of this second source.

The first thing that is obvious from these figures is that for virtually all technologies the correlation between the adoption rate and the log of real GDP per capita is positive. In fact, for some of these technologies the correlation is around 0.8. This is true, for example, for phones, televisions, and cars.

Secondly, the correlation seems to be diminishing for most technologies that are in their maturity and declining phases. This is most obvious for Bessemer steel, telegrams, steam and motor ships, rail transportation, and aviation. This suggests that for the rate of adoption in the early stages of a technology's life cycle is in large part determined by the level of economic development of a country. However, long run differences in adoption rates are for a much larger part determined by country specific factors that are not correlated with economic development. Which factors this might possibly be is part of the empirical analysis in Section 5.

What is interesting to notice is that the only two technologies that are negatively correlated with real GDP per capita in the early stages of their life cycle are OHF and BOF steel production. These are two of the few technologies that were not invented in the leading economies. That is, OHF steel originated in Germany in 1867 while BOF steel was invented in Austria in 1950.

Figure 4 lists the major innovations that spurred the technologies that we study in this paper. Each innovation is listed with the year and country in which it occurred. To relate these inventions back to economic development, we have listed them in chronological order and linked them to the time series for log real GDP per capita.

Of the four innovations before 1800, two occurred in continental Europe, one in Britain, and one in the U.S.. In the first half of the Nineteenth Century most innovations occurred in Britain, which was the economic leader at the time. The industrialization of Germany in the second half of the century led to the invention of OHF steel and the automobile. Most remarkable about this list of innovations, though, is that eight of the ten major innovations listed for the Twentieth Century took place in the U.S., which was the economic leader at that time.

Trickle-down diffusion

The big picture that follows from the descriptive statistics in this section is very much one of 'trickle-down' diffusion. That is, the evidence in this section leads us to think that most innovations happen in the economically leading country. After the invention, the new technology gradually trickles down from the economic leader to lagging countries. Our impression that it is leading economies that do most of the inventing is based on Figure 4. The positive correlations between technology adoption and real GDP suggest that rich economies do not only do the inventing but also lead in the adoption of new technologies. Finally, the trickling down of the technologies is confirmed by the catch up dynamics that we documented using both measures of β- and σ–convergence.

What is remarkable about this picture is that it seems to be robust across technologies. That is, even though we consider a set of heterogeneous technologies, the facts on which this trickle-down scenario is based seem to be remarkably similar for these technologies. Our conclusion is thus that this process is not due to technology specific properties, regulations, and anecdotes. Rather, this process is the result of some of the fundamental forces driving international technology diffusion.

Since trickle-down diffusion seems to be such a stylized fact across technologies, it is worth considering which types of theories would be consistent with this observation. This brings us back to Table 2. The colums of this table represent the two different answers to the question 'which countries invent new technologies and adopt them first?'. The evidence presented in this section points towards the richer economic leaders, rather than the poorer laggards. This is both true for the inventions as well as the lead in the adoption of new technologies.

Therefore, if we consider theories that aim to explain cross-country differences in technology adoption, total factor productivity levels, and real GDP per capita levels, these are more likely to be successful in replicating the important facts when they can be classified in the left-hand column of Table 2 rather than in the right-hand column.

Locking or no locking, that's the question

Now that we have argued that the descriptive statistics for our data set suggest that the left-hand column of Table 2 is empirically the most relevant, it is time to consider which of the rows of Table 2 most accurately reflects the answer to the question posed. This means that we will have to determine the answer to the question whether it does or doesn't take relatively long for a new technology to dominate existing ones.

Right off the bat, we can say that the fact that it takes most countries a significant amount of time to start collecting data on the adoption of new technologies indicates that there is a substantial delay before the new technologies become the dominant ones.

Unfortunately, our data do not suffice to address this question in more detail for all the technologies that we study. Therefore, we will have to limit ourselves to a bit more anecdotal evidence when addressing this issue.

Our first anecdote involves the growth contributions of different types of ships to the total of tonnage of the merchant fleet in the United States.

Let x_{ijt} be the total tonnage of ships of type j in the merchant fleet of country i at time t. Then

$$X_{it} = \sum_{j} x_{ijt} \tag{2}$$

is the size of the merchant fleet (in tonnage) in country i at time t. We calculate the growth contribution of ships of type j to this total between times t and $t+1$ as

$$g_{ijt+1} = \frac{x_{ijt}}{X_{it}} \frac{x_{ijt+1} - x_{ijt}}{x_{ijt}} \tag{3}$$

These growth contributions are of interest, because they provide useful insights into the degree to which countries are locked into old technologies.

In the most extreme case there is no gross investment in any of the non-frontier technologies as soon as a new technology is introduced. This means that all investment is in the frontier technology. In that case, as soon as a new technology is introduced all of the growth in the capital stock will be due to investment in this new technology. That is, $g_{ijt} \leq 0$ for all non-frontier technologies. Figure 5 plots the growth contributions of sailships, on the one hand, and steam- and motorships, on the other, to the growth of the U.S. Merchant fleet for 1820-1940.

The first steamship was built by Fitch in 1788 in Philadelphia. In the early years of their development steamships were relatively inefficient because they would consist of a steam engine put in a wooden hull. The first iron steamship was built in Britain in 1822. It took until 1843 before an iron ship crossed the Atlantic. However, as can be seen from Figure 5, it was only around 1875 before the growth contribution of steamships to the merchant fleet dominated that of sailships. This is more than 85 years after the steamship was invented.

In fact, the size of the U.S. merchant fleet in the nineteenth century peaked at a size of 5.5 million tons at the beginning of the Civil War in 1861. However, right after the Civil War, in 1866, the size of the fleet had declined by 22% to 4.3 million tons. This decline was fully attributable to the destruction of sailships during the war. The North used merchant ships for both a blockade of Confederate ports as well as other military operations. More than 600 merchant vessels were used by the Navy for military transportation purposes. In response, the Confederates started raiding merchant vessels and destroying them. Most of these vessels were sailships. After the Civil War the sailfleet never recovered from these losses and was slowly replaced by steamships. Gross investment in steamships seems to have continued for a while though. Harley (1973) documents how the wooden shipbuilding industry output, most of which were sailships, in the U.S. was still more than 200 thousand tons in 1890.

The U.S. is not an exception in its delayed adoption of steamships. In fact, it was one of the leaders. It simply took steam propulsion more than 75 years to become the dominant technology over sailing. Similar delays have been documented for other technologies as well, like BOF steel (Adams and Dirlam, 1966) and ring spindles (Saxonhouse and Wright, 2000).

There is another way of looking at locking effects. The locking versus no locking hypotheses can also be distinguished when we consider the response of a country to major capital destruction. If a country is not locked into non-frontier technologies, it will respond to capital destruction by replenishing its capital stock with structures and equipment that embody state of the art technologies. Germany's post-WWII experience provides a natural experiment that would allow us make inference about the degree of locking observed.

If there would be little or no locking, then it must be the case that Germany's post-WWII capital and output distributions across technology vintages would be more skewed towards modern technologies than that of its European counterparts. We consider whether this holds for Germany's merchant fleet and for its steel production. Figure 6 plots the steel output shares and shipping capital shares for Germany and some of its European counterparts.

The share of steel output for Germany and for the rest of Europe are plotted in the top two panels of Figure 6. Since these are shares, one cannot see from the figures how much more the German economy suffered during the war than that of other European countries. German steel production (for West-Germany) was 86% lower in 1946 than it was in 1938. On the other hand, for the rest of Europe steel production was 36% lower in 1946 than in 1938. In spite of this difference, the disproportionate destruction of German productive capacity did not result in Germany subsequently using more modern steel production processes than other European countries.

This can be seen from the top two panels of Figure 6. In the fifteen years following the war Germany's steel production grew by 375%. In the other European countries for which we have data it grew 85%. This excess growth in German steel production was not due to the Germans producing a bigger share of it with more advanced technologies. In fact, German steel production during this period relied more on Bessemer steel production than that in the rest of Europe, where OHF steel and EAF steel production was more widespread.

The same can be observed for the composition of the German merchant fleet. Data for this composition start in 1949 and we compare them with those for three Scandinavian countries (Denmark, Finland, and Norway) for which we also have data that distinguish between sail-, steam-, and motorships. In 1949 the German fleet consisted disproportionately of sail- and steamships. This was the result of heavy German losses during the war that especially affected their fleet of motorships. The (West-)German merchant fleet was rebuilt in rapid pace after the war. It grew by 1471% between 1949 and 1960, compared to 105% for the Scandinavian countries. However, as can be seen from the bottom two panels of Figure 6, this unprecedented growth of the German merchant fleet did not result in the Germans owning relatively more motorships than the Scandinavian countries.

Hence, both for steel production as well as for merchant shipping our evidence seems to suggest that after WWII the Germans were still locked into prewar technologies and did not upgrade their productive capacity more rapidly than other European countries.

Therefore, our examples indicate that investment in non-frontier technologies is an important empirical reality in cross-country technology adoption. Consequently, we feel that theories that can be classified in the top row of Table 2 are more likely to capture important causes of cross-country technology adoption disparities than are theories in the bottom row.

The next section is intended to give an overview of the main theories of technology adoption and diffusion and classify them in terms of the two questions posed in Table 2.

4. Main theories of technology adoption and diffusion

Throughout this paper we will distinguish five main theories/hypotheses about factors that determine technological adoption. In this section we describe these main theories and the relevant theoretical and empirical studies that relate to them. We illustrate several of these theories with an empirical anecdote, similar to one presented in the existing literature. Each of these examples is taken from the HCCTAD. Doing so serves two purposes. First of all, it allows us to present and discuss some of the anecdotal evidence on which a large part of the literature on technology adoption is based. Secondly, we use this section to classify theories in terms of the cells of Table 2.

Vintage capital theory

The workhorse of most macroeconomists that try to understand the adoption of new technologies is the vintage capital model. Since the early contributions of Johansen (1959) and Solow (1960), vintage capital models have proven to be a useful framework within which to jointly study the growth of the capital stock along both its extensive and intensive margin. The growth of the capital stock along the intensive margin in vintage capital models is caused by the assumed persistent growth of the quality of capital goods that are being added to it.

Most vintage capital models, like those by Johansen (1959), Solow (1960), Gilchrist and Williams (2000,2001) and Laitner and Stolyarov (2002), imply or assume that firms/countries do only invest in the frontier technology. Hence, once the new vintage is introduced there is no additional gross investment in older vintages and the part of the net capital stock embodying these older vintages decreases because of depreciation.

This means that, in terms of Table 2, vintage capital theory falls in the bottom row in the sense that it implies that new technologies instantaneously dominate existing ones. In reality, however, for the technologies in our sample that allow us to test this implication this does not seem to be the case.

As we have seen in the previous section, many technologies have very long implementation lags. Differences in these lags across countries could be an important source of technology adoption disparities. Yet, vintage capital theory is not able to explain these differences since it assumes that these lags are zero.

Though vintage capital theory does not provide us with insights into technology adoption disparities due to adoption lags, it does provide an explanation for the rapid rate at which Germany and Japan caught up with the U.S. and other industrialized countries in the post-WWII decades.

Gilchrist and Williams (2001) argue that this catch up is more consistent with a putty-clay vintage capital model than with the standard neoclassical growth model. The intuition behind their result is that the productivity growth in Germany and Japan in the decades after WWII is consistent with these countries replacing the destructed capital with more modern vintages and therefore having a more 'modern' capital stock than countries that were not subjected to this capital destruction. However, as we saw in the second empirical example on technological locking in the previous section, this does not seem to have been the case.

In sum, vintage capital theory is useful to jointly consider the mechanisms underlying technology adoption and capital accumulation. However, much of the current vintage capital literature does not allow us to explain technological adoption disparities between countries. It fails to capture two important facts about cross-country technology adoption emphasized in Table 2, namely that rich countries tend to be the first to adopt new technologies and that this adoption only gains momentum after a significant lock-in period in which investment in and the use of non-frontier technologies seems to dominate.

Vintage human capital

We are not the first to observe that investment in non-frontier technologies tends to persist for a while after a new technology is introduced. In fact, this observation spurred a flurry of theoretical models that we will simply designate as vintage human capital models. Examples along this line are Chari and Hopenhayn (1991), Brezis, Krugman and Tsiddon (1993), and Jovanovic and Nyarko (1996).

All vintage human capital models have one important component in common. The use of a technology results in technology specific experience, known as vintage human capital. Such experience will reduce the incentive to update to new technologies, because doing so would lead to the loss of the value of this experience. Consequently, workers and firms will hang on to older technologies and continue to invest in them even though newer and potentially better ones are available.[6]

There are empirical examples of vintage human capital effects abound. Harley (1973) argues that wooden shipbuilding in the U.S. persisted because of the specific skills involved in wooden shipbuilding and because a lagging supply of skills needed to build iron ships. In the U.K., on the other hand, the latter skills were more abundant, resulting in a relative cost-advantage for metal ship building in the U.K.. Robertson (1974) follows up on Harley's (1973) argument by documenting the decline in the apprenticeship system in the U.K. that was used for centuries to transfer the skills and knowledge needed for wooden shipbuilding. When technological progress increased and iron shipbuilding became more common, the knowledge of the older generation that was supposed to teach the apprentices was largely outdated. For the part that it wasn't, apprentices attained the skills and then left for better paid jobs after having been educated because of the lagging productivity in the wooden shipbuilding industry.

[6] Jovanovic and Nyarko (1996) even provide a theoretical example where the productivity loss due to the scrappage of experience is so large that workers could be permanently locked into using non-frontier technologies.

Another, often referred to, example are the different predominant spinning technologies in the Nineteenth Century in the U.K. and the U.S.. While textile producers in the former tended to opt for the mule spindle, the ring spindle became more popular in the latter. Technologically, the difference between the two is that ring spindles spin continuously while mule spindles spin intermittently. Because of the intermitted nature in which they operate, mule spindles require the workers that operate them to have some very specific skills. According to Saxonhouse and Wright (2000), the initial divergence between the spinning technologies used in the U.K. and the U.S. can be traced back to two elements. Most important was the relative scarcity of a "stock of skilled mule spinners to draw upon" in the U.S. compared to the U.K.. Secondly, there was a difference in the degree of standardization of the output produced in each country. According to Saxonhouse and Wright (2000), "Ring spinning was well suited for long-staple American cottons that were used in the relatively power-intensive production runs of standardized yarn and cloth for the domestic market. By contrast, the mule was better adapted to variations in cottons and yarn counts, and thus allowed Lancashire to take advantage of its proximity to the world's largest cotton market in Liverpool, and to produce for diverse buyers all over the world". For decades, learning-by-doing effects amplified these differences between the U.S. and the U.K.. These differences lasted until after WWI, when additional innovations in ring spindles turned them into the unambiguously preferred spinning technology.

Vintage human capital theory can provide us with useful insights into adoption delays for those technologies that replace ones that led to the accumulation of a technology specific skill-set. Shipping and textiles are an example of this. However, in the previous section we also presented evidence on adoption lags for steel production. For steel it is much harder to argue that its various production processes require many technology specific skills. In fact, BOF steel production is very similar to Bessemer steel production except that it uses pure oxygen rather than hot air to remove carbon impurities from the iron ore.

There is one important reason why it is unlikely that vintage human capital mechanisms are the predominant force underlying the observed adoption lags. If it would be vintage capital effects, then, as Brezis, Krugman and Tsiddon (1993) illustrate, we would see leapfrogging in terms of the adoption rates of various technologies. That is, just like standard vintage capital theory, vintage human capital theories predict that countries that are the most intense users of existing technologies and have built the most technology specific skills are the countries that have most to lose from switching to new technologies. This would suggest that we would observe leapfrogging as well as a negative correlation between technology adoption rates and real GDP per capita in our sample. In terms of Table 2, vintage human capital theory can be classified in the upper-right hand cell. However, our evidence presented in the previous section suggests that theories in the upper-left cell would be most likely to do a good job at explaining the observed cross-country technology patterns.

Innovator-Imitator models

Vintage human capital models are intended to explain the adoption lags that we observe for many technologies and that are not captured by the standard vintage capital model. Imitator-innovator models are aimed at explaining the fact that leaders tend to innovate and to be early adopters while the lagging countries mostly imitate. This is another fact that is not explained by the standard vintage capital model.

The two most notable models in this category are Barro and Sala-i-Martin (1997) and Eeckhout and Jovanovic (2002). Barro and Sala-i-Martin (1997) consider a two-country version of Romer (1990) in which one country is an innovator and the other an imitator. An imitation cost leads to the imitating country persistently lagging the leading country in the adoption of new production methods. Eeckhout and Jovanovic (2002) consider a model with a continuum of ex ante identical agents/firms. Each of these agents can choose between innovating or imitating with a certain delay. The steady state equilibrium outcome of the model is a distribution of TFP levels relative to the leader in which this shape of this distribution is determined by the technology adjustment cost and the cost of imitating.

Both of these models explain why imitation costs might result in imitators trailing the innovators and both of these models generate an equilibrium outcome in which the (richest) technological leader is the one to innovate and the first to adopt. Subsequently, others will follow. However, from an empirical point of view, these models fail to provide us with potential explanatory variables for the equilibrium adoption disparities that they generate. That is, in Barro and Sala-i-Martin (1997) it is predetermined which country is the leader and which is the imitator. What constitutes the innovation costs not addressed. This is the same for Eeckhout and Jovanovic (2002). Their model actually assumes that all agents are ex-ante identical and the only ex-post difference between them is essentially their TFP level.

Consequently, even though these models provide us with a theoretical framework that can be classified into the, empirically most relevant, left column of Table 2, they do not provide us with an extensive basis for our empirical analysis which aims to identify determinants of adoption disparities.

GPT with complementary inventions

There is actually a theory that can be classified in the, empirically most relevant, upper-left cell of Table 2. It is Helpman and Trajtenberg's (1998) model on the diffusion of General Purpose Technologies (GPTs). In their model GPTs arrive exogenously. Countries/sectors which are able to use them with the least expenditures on complementary innovations and can expect the biggest demand shift when adopting the GPT are the early adopters in their model. The adoption only takes place with a delay, after the complementary innovations are implemented. In the simplest theoretical framework, the early adopters are the same countries/sectors for all GPTs.

Even though Helpman and Trajtenberg's (1998) model is able to generate the two stylized facts that we observe for cross-country technology adoption patterns, it does not provide us with many potential candidate variables that explain the adoption delays. One could argue that some technologies cater to certain languages. This seems especially true for personal computers. Hence, countries where a small fraction of the population speaks English face higher costs, in terms of complementary innovations, of implementing personal computers. Caselli and Coleman (2001), however, find that this effect is negligible. It is simply not clear why the degree of variation in the extent of the complementary innovations needed for the adoption of new technologies across countries would be so big that it is a major force driving cross-country adoption disparities.

Factor Endowments

So, what are the empirical variables that economic theories of cross-country technology adoption suggest as candidates for explaining cross-country adoption disparities? First and foremost, there are factor endowments that are measured as part of conventional factors of production, namely physical and human capital.

Factor endowments may affect the speed of adoption of new technologies for three reasons. If technology and the factor of production are complementary, then the marginal value of the new technology will be increasing in the level of the factor. This would lead to countries with high factor endowments to adopt technologies first. Theoretical models that generate such a technology adoption mechanism are Jovanovic (1998) and Hobijn (2001).

The polar case is when technology and the relevant factor are substitutes. Firms have higher incentives to invest in factor savings technologies when the price of the factor is relatively high. Acemoglu (2001) contains a theoretical framework that formalizes this argument.

Finally, Basu and Weil (1998) introduce a model of appropriate technology. In their model, new technologies can only be implemented successfully by countries with the appropriate portfolio of endowments.

What these theories of factor endowments and technology adoption have in common that they explain different technology choice decisions as efficient responses to differing compositions of endowment portfolios of firms and countries.

Contrary to the innovator-imitator models, the theories on technology adoption and factor endowments pinpoint potential factors underlying technology adoption differences. In fact, the available empirical evidence suggests that factor endowments are definitely part of the story.

Caselli and Coleman (2000) as well as Lee (2000) document the capital-skill complementarity for computers at a cross-country level. They find that high levels of educational attainment are important determinants of computer-technology adoption, even after controlling for a variety of other macroeconomic variables. This effect is quantitatively important. A 1 percentage-point increase in the fraction of the labor force that has better than primary education leads to an increase in computer investment per worker of roughly 1 percent. Capital-skill complementarities might not be the only mechanism that generates this covariation. Benhabib and Spiegel (1994) document how human capital endowments actually affect the speed at which countries seem to be able to absorb technological developments.

Historical examples of factor saving technological change are plenty. The relative scarcity of labor in the U.S. textile industry compared to the U.K. led to an accelerated adoption of automatic looms. The use of automatic looms dates back to the pre-1914 era. Yet in 1946 only 6% of the looms in use in the UK were automatic types compared to 70% in the United States.

Jerzmanowski (2002) decomposes cross country TFP differences in a part that can be attributed to factor differences and a part that contains efficiency differences between countries that are unexplained by their factor endowments. This decomposition suggests that factor endowments explain part of cross-country TFP differences between countries. However, the bulk of these differences cannot be attributed to differences in their conventionally measured endowments.

Hence, both theory and empirical evidence suggest that factor endowments are partly driving cross-country technology adoption mechanisms. However, they are definitely not the whole story. It is therefore worthwhile to consider other potentially relevant variables.

Trade

Trade might affect the rate of technology adoption in a country through both a push and a pull effect. The push effect is emphasized in Grossman and Helpman (1991) in the sense that countries that import goods from countries that are more technologically advanced get more exposure to new technological developments and will, consequently, be more likely to adopt the technologies that they are exposed to. That is, high-tech imports tend to 'push' the knowledge down the trade channel.

Most of the evidence in support of this hypothesis has been documented for R&D spillovers on cross country TFP levels. Coe and Helpman (1995), Coe et al. (1997), and Lichtenberg and Pottelsbergh de la Potterie (1998) all provide evidence on how countries whose trading partners invest more in R&D seem to have higher TFP levels than other countries. This seems to hold both within the OECD as well as for a much broader sample of countries.

Besides the push effect of trade mentioned above, there is the pull effect. Holmes and Schmitz (2001) model this pull effect. Their model considers the case in which domestic producers in a country spend a significant chunk of resources on protecting themselves from their domestic competitors. However, these resources are not successful in the protection against foreign competition. Consequently, when trade barriers are lifted, these domestic producers shift from their protective activities to the more productive innovative activities that are necessary to sustain their international competitiveness.

There is definitely evidence that domestic producers beef up their productivity to remain competitive in response to trade liberalization. For example, Boer et. al. (2001) show that this is the case for Turkish producers in response to the Turkish trade liberalization.

Hence, theories and evidence suggest that, for technology adoption, it both matters how much countries trade and are exposed to the competitiveness of international markets as well as with whom they trade and from whom they benefit from spillovers. Furthermore, the push and pull channels combined suggest that both imports and exports might matter.

Both the push effects that are emphasized by the spillover studies as well as the pull effect modeled by Holmes and Schmitz (2001) suggest that the effect on trade on technology adoption is not fully endogenized in the trade decisions. This suggests that the effect of trade on technology adoption partly reflects inefficiencies that are caused and could possibly corrected by active trade policies.

Vested interests and political institutions

Creative destruction creates winners and losers. Those whose economic, political and social interests are threatened by the adoption of new technologies are likely to put effort in the prevention of their diffusion or will try to appropriate some of the rents that these technologies yield.

Disgruntled displaced workers might try to prevent the adoption of new labor saving technologies. For example, the first major innovation in textiles manufacturing affected the productivity of weavers. In 1733 the Flying Shuttle was invented by John Kay. Before the Flying Shuttle weavers were only able weave cloth that was about three feet wide. Wider cloths needed more than one weaver. The Flying Shuttle allowed weavers to speed up their weaving process as well as expand the width of the cloth that a single weaver could handle. Because of the labor-saving nature of his invention Kay faced a lot of resistance from weavers. In 1753 his house was wrecked by them. Kay was not the only inventor of the industrial revolution whose property was wrecked by workers that felt threatened by their inventions. Richard Arkwright was the inventor of the water frame. It was the first economically viable machine that allowed for mechanized continuous spinning. Even though Arkwright accumulated half a million pounds and could be considered the World's first industry mogul, success came with the necessary resistance. In 1768, for example, his mill at Chorely was destroyed by an angry mob of spinners.

It is not uncommon for the suppliers of technologies to use their economic and political cloud to maintain or expand their market power. Some, like Snell (1974), have argued that this was the case for the car industry and its way of dealing with public transportation companies in many American metropolitan areas. At the end of WWII National City Lines, a company largely controlled by General Motors, Standard Oil of California and Firestone Tire, controlled 46 major transit networks in the U.S.. It decided to phase out electric trolleys and replace them with diesel-powered buses. In 1949 the companies that had owned National City Lines were convicted of conspiring to replace electric transportation with buses and to monopolize the sale of these buses. Each company had to pay a token-fine of $5,000 each.[7]

One trivial corollary to these examples is that the presence of these barriers to technology adoption is going to be an important deterrent to the adoption of new technologies.[8] To go beyond this obvious statement we should understand what political and legal regimes are more propitious for the enforcement of property rights.

On this front there is a recent literature that tries to endogenize some aspects of the political institutions by arguing that agents select the optimal institutions. For example, Comin and Beunza (2003) build a model where feudal bonds arise when there is a need to transfer power to the lord in order to induce him to invest in in defense. Hanssen and Fleck (2003) rationalize the genesis of democracy in ancient Athens by arguing that in order to induce peasants to undertake highly productive, non-observable investments in preparing the fields to cultivate olives they needed to have control over the political system and in this way prevent the expropriation of their investments. Similarly, Lizzeri and Persico (2003) argue that the extension of the franchise in eighteenth century England was induced by a majority of the elite that found more attractive spending public resources in the provision of public goods (like a sewage system) instead of in personal transfers to a minority of the elite. These last two contributions seem more relevant for the period covered by

[7] In spite of this conviction, it is not quite clear whether without National City Lines electric trolleys would have lasted much longer in most of these markets, or, as Rasmussen (2003) argues, that National City Lines simply accommodated the inevitable demise of these trolleys. However, independently of whether the sentence is fair or not, this example illustrates the importance of the role played by vested interests and the judicial system in the adoption of technologies.

[8] It is also likely to be an important determinant of the level of development. Parente and Prescott (1994,1998) illustrate how adoption barriers and monopoly rents lead to cross-country variation in TFP levels and how the demolition of these barriers can lead to astounding growth miracles. Landes (1969, ch.1), Jones (1981), and North (1981) also support the view that relates property right enforcement to economic development.

the HCCTAD and imply that democracies are better at preserving property rights and deterring interest groups from benefiting a majority of society, for example, by preventing the adoption of new technologies.

Another interesting hypothesis comes from the legal tradition. Several judges and courts have expressed the view that a strong judiciary system may prevent the legislative power from passing the laws that enact the deterrent actions conducted by vested interests. Indeed, between the late nineteenth century and the early 1930s hundreds of laws were rendered obsolete by sentences of the judiciary that were based on the idea that they favored interest groups impeded individual rights. For example, the U.S. Supreme Court in Lochner vs. New York sentenced that:

"The limitation of employment in bakeries to 60 hours a week and 10 hours a day, attempted by Laws N.Y. 1897, c. 415, art. 8, § 110, is an arbitrary interference with the freedom to contract guarantied by Const.U.S.Amend. 14, which cannot be sustained as a valid exercise of the police power to protect the public health, safety, morals, or general welfare."

In the same line, the takings cases argue that it is necessary for property rights to have protection on a constitutional level, meaning that they will be protected by judges and that the legislature cannot interfere with them absent a constitutional amendment.

A related view was expressed by James Madison (1787 and 1788) in the Federalists papers where he argues that local government is likely to expropriate property rights while distant, indirectly elected government will more effectively serve the interests of the country, because it will be insulated from localized factions that will dominate local government and demand property redistribution and cancellation of debts. Both indirect governments and the judicial system, unlike the senate or local governments, are distant institutions that are isolated from vested interest and therefore should base their decisions on what is best for society.

5. Panel data analysis

Now that we have considered which theories are the most likely candidates to explain the trickle-down diffusion dynamics with technology lock-ins that we observe in the data, it is time to consider the determinants of the rate at which technologies are adopted and trickle down.

In this section we will address this issue through the application of several panel data regressions. These regressions are intended to provide insight into which variables determine the cross-country technology adoption disparities that we observe. Since the countries that trail in the adoption of new technologies are those to whom these technologies trickle down the slowest, such a regression implicitly identifies the variables that determine the relative speed at which technologies trickle down.

This section consists of three parts. In the first part we describe the data and basic regression specification that we use. In the second part present the results from a set of regressions that pool the data both across technologies and over time. Finally, we present how our results vary when the data are not pooled across these dimensions.

Data and regression specification

Since our aim is to consider the determinants of cross country technology adoption disparities, our dependent variables are based on the technology measures introduced in Table 1. To remain consistent with the coefficients of variation that we presented in Section 3, we consider the disparities in the logarithms of these measures. In order for our analysis to be less sensitive to business cycle fluctuations that are not part of the growth process that we are trying to capture we consider the logarithm of five-year averages of the technology adoption variables. This means that the frequency of observation along the time dimension in our panel is once every five years.

Our dataset has three dimensions which we will index by *i* for the country, *j* for the technology, and *t* for the time period. Let Y_{ijt} denote the technology adoption measure *j* for country *i* at time *t, where this measure is in logs whenever the variable is not a share*. All the empirical results that we present will be for regression equations of the form

$$Y_{ijt} = d_{jt} + \sum_{k=1}^{m} \beta_k X_{ijkt} + e_{ijt} \tag{4}$$

where d_{jt} is a technology specific time dummy and X_{ijkt} for $k=1,\dots,m$ are the covariates that we consider as potential determinants of technology adoption.

The dummies d_{jt} demean the technology adoption measures for each technology in each period. This means that the deviation Y_{ijt}-d_{jt} reflects the technology adoption disparity of a country from the average adoption rate across countries.

The covariates that we use can be classified into five categories. Table 5a contains a list of all the covariates that we consider in our analysis. The classifications of the variables are as follows. (*A*) standard variables which contain the dummies and the logarithm of real GDP per capita. We include the latter in order for it to capture both income effects that inherently contribute to the different rates of technology adoption as well as endowment differences across countries that are omitted in the other variables. (*B*) Human capital endowments, consisting of enrollment rates and attainment rates. (*C*) Trade variables that include openness and measures of the level of development of a county's trading partners. The latter are the trade-weighted levels of $\ln Y_{ijt}$ for the trading partners of a country and the trade-weighted logarithms of real GDP per capita for the trading partners. Each trade weight consists of the exports and imports of a country to and from a specific trading partner divided by total trade of that country. All trade data are measured in 1000's of current U.S. Dollars. (*D*) Institutional variables that take into account the type of executive authority, the type of regime in a country, the degree of party fractionalization and the effectiveness of the legislative. (*E)* Technology interaction terms, which are used to probe the influence of the sequential nature of many of the technologies in our dataset on the cross-country adoption disparities.

Just like Caselli and Coleman (2001) and Lee (2000), we do not think that simultaneity bias is a particularly big problem for the regression results that we present in the following. The reason is that these regressions try to explain the adoption of (micro-) technologies by considering overall macroeconomic factors. This is an important advantage of having the level of adoption in some specific technologies as the dependent variable (instead of GDP per capita or TFP). It is hard to argue that the number of letters per capita, or the number of cars per capita affect the type of regime, the degree of openness or the enrollment rates in the country, or even have an immediate effect on GDP.

Further, since in our regressions we will be controlling for GDP per capita, we believe that it is hard to argue that the correlations that we find between the intensity of technology adoption and policy, institutional or human capital measures are driven by omitted variable biases.

For this reason we will abstain from using any instrumental variables, except for the trade weighted levels of technology adoption of a country's trading partners and for the previous technology. In both cases the instrument that we use is the five-year lagged value of the variables.

This identification strategy has the advantage that it allows us to estimate the impact of both the endogenous and the exogenous components of institutions, policies and human capital. As a result, the analysis yields some policy recommendations that are not so dependent as a pure instrumental variable strategy on the assumption that the effect of the endogenous component of the regressors has the same impact as the exogenous one.

The panel structure of our data set has several important advantages over cross-sectional data sets. First of all, the data captures time variation as well as cross-sectional variation in the variables. By exploiting the variation in both dimensions, our data are more suitable to identify the effect of variables such as institutions that do not have much variation in the cross-section. Secondly, because our data set covers many different technologies and a long time span, we are able to consider the robustness of our results across technologies and over time.

This is what we will do in the following. First we will present a set of results that pools our sample of technologies and considers the whole sample period, then we introduce technology specific results as well as separate results for the pre-WWII and post-WWII periods.

Pooled regression results

Our approach will be to present regression results for a broad number of selected specifications and to emphasize what they have in common. These specifications are selected because they reflect the general results that we obtained using our set of explanatory variables. Because some variables that we consider are not available for all time periods and all technologies the dependent variables in the regressions are not always the same across specifications. The advantage is that this allows us to include a broad range of covariates. The disadvantage is that it makes goodness of fit comparisons between specifications hard to interpret. For this reason, we will focus on the size and significance of the relevant regression coefficients rather than test specifications against each other.

Table 6 contains the regression results of the pooled regressions. In the table the variables are grouped according to their classification in Table 5.

The logarithm of real GDP per capita, classified under A, turns out to be significant across all specifications. Its coefficient is mostly slightly bigger than one, suggesting that, conditional on other variables, countries with a 1% higher standard of living are 1% ahead in technology adoption. In fact, it turns out that real GDP on its own explains a surprisingly large part, 23.7%, of the cross-country technology disparities in our data set. Real GDP per capita is not the only thing that matters, though.

Our regressions suggest an important role for education as well. Our data contain four measures of enrollment rates. It contains primary and secondary enrollment rates for pre-1970 and post-1970. The split between the two periods is because of data availability limitations. Enrollment rates, specifically secondary enrollment rates, turn out to matter much more before 1970 than after 1970. Especially for pre-1970 secondary enrollment rates we find that they have a significant and large impact on adoption patterns. In fact, our results suggest that a 3% increase in secondary enrollment would lead to approximately a 1% increase in technology adoption. There are probably two reasons why secondary education turns out to be most important. First of all, there is much less variation in primary enrollment rates than in secondary enrollment rates. Furthermore, skills required for the use of most of the technologies in our sample go beyond the basic ones acquired in primary school. After 1970 it seems that the attainment rates do a better job capturing the skill requirements of new technologies. The attainment rate that matters most is that for tertiary education. This is consistent with the view that modern technologies, like personal computers, especially complement college level skills. See Heckman et. al (2003), for example, for a set of estimates of the increase in the college skill premium since 1950.

Of the various trade-related variables that we consider the most straightforward one, namely openness, seems to matter the most for adoption. Consistently with the theory, countries whose trade makes up a larger part of its GDP turn out to be the frontrunners in technology adoption. The coefficient on openness is significant for the bulk of our specifications and its magnitude implies that countries that are 12%-15% more open than others will be 1% ahead in the adoption of technologies. Coe and Helpman (1997) find a strong effect of the technological advancement of the trading partner on TFP. Surprisingly, the trade-weighted averages of GDP and the level of technology adoption for the trading partners turn out to have a negative effect, even when interacted with openness.[9] This result seems to indicate that the effect of trading with a technologically advanced partner on TFP does not operate through a more intensive adoption of the advanced technologies. If this result is correct, the relevant channel must be the disembodied component of TFP. By trading with a more advanced partner, a country may benefit from his superior knowledge and, in this way, facilitate the development of more appropriate complementary inputs or learn the managerial practices that are better suited for the used technology.

There are four types of institutional variables that have important effects on the intensity of technological adoption. The first two have to do with the type of political regime. The first, ex.other, is the one that identifies countries with effective executives that do not have a formal government post or in which a national executive does not exist. The second identifies military regimes. We find that both of these attributes of the political institutions have large, negative effects on technology adoption. There might several ways in which the lack of an executive structure might affect adoption. Most importantly, an executive structure is necessary for the implementation and enforcement of property rights and can be held accountable for abuses of political and economic powers of interest groups. Countries that do not have a well-organized executive

[9] The latter was suggested by Lichtenberg and Pottersberghe de la Potterie (1998) when considering the effect of the R&D stock of trading partners on a country's TFP level.

branch are most prone to infringe on the returns to technology adoption through the channels that we discussed in Section 4.

Another variable that seems quite important to understand the technology adoption dynamics is the effectiveness of the legislative. We find that an effective legislature delays the adoption of technologies. This is consistent with the vested interest theories that argue that incumbent innovators have incentives (and power) to lobby the legislature to pass laws barring the adoption of new technologies. An effective executive is then in a better position to thwart the adoption process.

Finally, the last political dimension that we consider is the degree of party fractionalization. A more fractionalized parliament seems to enhance the adoption of technologies, though we have to be a bit cautious with this conclusion since most of the observations that we have correspond to the post WWII period.

One of the advantages of the HCCTAD is that by having information on several technologies we can investigate the existence of interactions across the adoption of different technologies. We consider two types of interactions. First, to check more formally the presence of leapfrogging, we study the effect of the intensity of adoption of the previous technology on the current technology. Prior to that, though, we identify for some of our technologies what was the previous technology in a quality ladder sense. These matches are reported in table 5b. The results reported in table 6 are very robust and confirm our observations in section 3. Leaders in the adoption of one technology tend to be leaders in the adoption of the successive technology. As we emphasized in section 3, this seems at odds with some vintage human capital models that predict the existence of leapfrogging. Instead, the simultaneous presence of lock in and absence of leapfrogging is consistent with models that emphasize the role of accumulated knowledge in the reduction of adoption costs (lock in) and at the same time allow for this knowledge to be (partially) transferable across technologies (no leapfrogging).

The second technology interaction that we consider is the effect of some general purpose technologies on the adoption of other innovations. In table 6 we report a strong positive effect of electricity production on the adoption of the other technologies.

Time and technology specific regressions

One of the advantages of having a three-dimensional data set is that we can cut the data along many dimensions to evaluate the robustness of the findings and uncover some new patterns that do not hold at the aggregate but that are robust for certain time periods, countries or technology clusters.

In table 7a, we divide the sample in two groups: those technologies that have a previous technology in our sample, and those that do not (share of ring spindles, railroad, electricity production and share of EAF steel)[10]. This division seems remarkably enlightening to understand the effect of trade openness and institutions. For the technologies with predecessors, we find that trade openness has a strong positive effect and that having a military regime, no visible executive and an effective legislature strongly jeopardize the process of technology adoption. For the technologies without a predecessor, we find that trade openness or institutions have no effect.

[10] Computers and robots are irrelevant for this analysis because the institutional variables only run through 1970 and, since they appear in sample around that date, they are automatically dropped out of the analysis.

We view these results as evidence of the deterrent role of vested interests for technology adoption. This interpretation hinges on our assumption that the adoption of technologies with an obvious predecessor is more likely to threaten vested interests than the adoption of technologies that do not have an obvious predecessor.

Similarly, the fact that trade openness only seems to matter for the technologies with a predecessor seems natural if we think that trade matters because it introduces the pressures of foreign competition on incumbents and, by doing that, reduces their payoff of lobbying to deter the adoption of new technologies.

The HCCTAD also allows us to go more micro and study the determinants of the disparities in technology adoption in more disaggregated technological groups. Table 7b does that for the eight groups presented in table 5a.[11] The most striking fact is the large amount of heterogeneity that we find across technologies. This heterogeneity is an important caveat for case studies that typically consider only a few technologies.

Despite that heterogeneity, there are some results that seem quite robust. The relevance of the logarithm of real GDP per capita is robust across technologies, except for shipping for which it is insignificant. Education seems to matter little or negatively for technologies that are not skill-intensive, like textiles, steel, and shipping. It is most significant, both statistically and economically, for the adoption of electricity (*VIII*), mass communication (*IV)*, and personal computers (*14*). For personal computers we find that tertiary attainment rates has much more explanatory power than primary or secondary ones. The regression for computers is consistent with the results presented in Caselli and Coleman (2001) who also find that per capita income and human capital are the main determinants of computer adoption. Having other executive seems to have a robust negative effect on technology adoption. Electricity production comes out positively for almost all the groups, the main exception being steel. We see some pull forces in steel, since railroad freight has a strongly positive effect on the adoption of innovations in steel production. Finally, the most interesting results in table 7b are related to the effect of the previous technology. We find that the adoption of the previous technology has a positive effect in transportation and mass communication. However, it has a negative effect on steel.

Finally, we can cut the data set along the time series dimension to evaluate how the determinants of the adoption disparities have evolved over time. A natural division is WWII. Table 8 contains the results for three regressions: one for the whole sample, one for the pre-1945 period, and one for the post-1945 period.

The regressions suggest that human capital played an important role in the rapid postwar catch up of many countries. Primary and secondary enrollment rates seem to have been important sources driving the rapid adoption of new technologies after WWII in some of the trailing economies. Our post-1970 measures of enrollment do not seem to explain as much as the pre-1970 ones. There are two potential reasons. First of all, this might be due because they are measured differently. Secondly and more importantly, it is also likely that since 1970 it is actually tertiary schooling that is most relevant for the adoption of technologies rather than primary and secondary schooling.

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[11] To maintain reasonable sample sizes, we do not include the effectiveness of the legislature and the party fractionalization index as regressors.

The importance of the legislative efficiency also increases after WWII, as well as the positive effect of openness on technology adoption. Note, however, that, as we observed in table 7a, openness does not come out significant once we control for electricity production when we pool together all the technologies. In regressions not reported here, we have observed that conditioning on the technologies with predecessor, trade openness has a significant effect that also becomes stronger after WWII.

Most of the variation in the type of effective executive and in the type of regime in our sample occurs in the pre-WWII. After WWII most countries have converted to parliamentary democracies where a premier is the effective executive. Military regimes were in power for periods in Greece, Japan, Spain, and Portugal. This lack of variation explains the decline in the significance of the type of effective executive and regime after WWII.

These results lead us to believe that the increase in the rate of technological catch up after WWII is caused by the increased degree of homogeneity between the industrialized leaders in the World. That is, since WWII the variation in barriers to technology adoption across the World's industrialized leaders has reduced, leading to a more synchronized adoption of new technologies.

6. Conclusion

Technology is an important determinant of cross-country variation in income per capita. In this paper we have presented a wide range of facts on the differences in the rates of adoption of 25 technologies across 23 of the World's industrialized leading countries. The facts presented depict a pattern of trickle-down diffusion that is remarkably robust across technologies. Most of the technologies that we consider originate in economically leading countries and are adopted there first. Subsequently, they tend to trickle down to lagging countries. We observe that it takes a long time before a technology dominates its predecessor. We also find that countries that lead in the adoption of a new technology also tend to lead the adoption of its preceding technology.

Our panel data regression results indicate that several factors have played an important role for the determination of the variation in the rate of adoption of technologies across countries. Human capital and income per capita have a positive effect on technology adoption throughout the sample. The type of executive and regime have played a more important role in the pre-WWII period. We also have found evidence that protection against vested interests either through an ineffective legislature or by opening the economy to trade enhances the adoption of new technologies. These effects seem to have been more important in the post-1945 period.

There seems to have been a remarkable acceleration of the speed at which technologies trickle down from leaders to followers during the postwar period. We conjecture that this process is associated with the convergence in the main determinants of technology adoption like openness, human capital or the type of regime across the sample of countries that we consider.

Our analysis in this paper focused on cross-country differences in the adoption of technology and ignored the evolution of the average adoption rate. Future research about the determinants of this evolution of the world technology frontier would be a useful complement to the results presented here.

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Table 1. Countries and technologies covered

Period covered: 1788 – 2001

	Countries		Technology measures
1.	Australia (AUS)	*I.*	*Textiles*
2.	Austria (AUT)	1.	Fraction of spindles that are mule spindles
3.	Belgium (BEL)	2.	Fraction of spindles that are ring spindles
4.	Canada (CAN)	*II.*	*Steel*
5.	Denmark (DNK)	3.	Fraction of tonnage of steel produced using Bessemer method
6.	Finland (FIN)	4.	Fraction of tonnage of steel produced using Open Hearth furnaces
7.	France (FRA)	5.	Fraction of tonnage of steel produced using Blast Oxygen furnaces
8.	Germany (DEU)	6.	Fraction of tonnage of steel produced using Electric Arc furnaces
9.	Greece (GRC)	*III.*	*Telecommunication*
10.	Iceland (ISL)	7.	Mail per capita
11.	Ireland (IRL)	8.	Telegrams per capita
12.	Italy (ITA)	9.	Telephones per capita
13.	Japan (JPN)	10.	Mobile phones per capita
14.	Luxembourg (LUX)	*IV.*	*Mass communication*
15.	Netherlands (NLD)	11.	Newspapers per capita
16.	New Zealand (NZL)	12.	Radios per capita
17.	Norway (NOR)	13.	Televisions per capita
18.	Portugal (PRT)	*V.*	*Information Technology*
19.	Spain (ESP)	14.	Personal computers per capita
20.	Sweden (SWE)	15.	Industrial robots per unit of real GDP
21.	Switzerland (CHE)	*VI.*	*Transportation (rail, road-, and airways)*
22.	United Kingdom (GBR)	16.	Freight traffic on railways (TKMs) per unit of real GDP
23.	United States (USA)	17.	Passenger traffic on railways (PKMs) per capita
		18.	Trucks per unit of GDP
		19.	Passenger cars per capita
		20.	Aviation cargo (TKMs) per unit of real GDP
		21.	Aviation passengers (PKMs) per capita
		VII.	*Transportation (shipping)*
		22.	Fraction of merchant fleet (tonnage) made up of sailships
		23.	Fraction of merchant fleet (tonnage) made up of steamships
		24.	Fraction of merchant fleet (tonnage) made up of motorships
		VIII.	*Electricity*
		25.	MWhr of electricity produced per unit of real GDP

Table 2. Two main dimensions of evidence (theory)

		Cross-sectional variation What type of country invents and adopts new technologies first? Rich countries/Leaders	Poorer countries/Followers
Time variation How long does it take for a new technology to dominate existing ones?	Long/ Locking	• GPT with complementary innovations Helpman and Trajtenberg (1999)	• Vintage Human Capital Chari and Hopenhayn (1988) Brezis, Krugman, and Tsiddon (1993)
	Short/ No locking	• Innovator-Imitator models Barro and Sala-i-Martin (1997) Eeckhout and Jovanovic (2003) • Technology choice with technology skill complementarities Jovanovic (1998) Hobijn (2001) • Appropriate technology Basu and Weil (1998) • Barriers to riches Parente and Prescott (1994,1999)	• Vintage Physical Capital Johansen (1959) Solow (1960) Gilchrist and Williams (2001) Laitner and Stolyarov (2002)

Table 3. Descriptive statistics – means and sample size

	Technology measure	number	Mean								sample size							
		(Table 1)	1880	1900	1920	1938	1960	1970	1980	1990	1880	1900	1920	1938	1960	1970	1980	1990
	Real GDP per capita		3.2	3.7	4.7	5.6	9.2	13.6	17.4	21.3	15	20	18	21	21	21	21	21
I.	Ring spindles	2				.80	.61	.83	1.00					7	11	6	1	
II.	Bessemer steel	3				.27	.23	.09	.00	.00				11	16	18	18	21
	OHF steel	4				.43	.43	.25	.06	.00				11	16	18	18	21
	BOF steel	5				.00	.07	.43	.66	.59				11	16	18	18	21
	EAF steel	6				.30	.26	.23	.28	.41				11	16	18	18	21
III.	Mail	7	28.5	62.6	91.5	113.8	154.9	181.4	207.8	283.7	15	18	16	17	20	21	20	19
	Telegrams*	8	0.64	1.07	1.77	1.01	0.89	0.61	0.30	0.19	16	18	18	18	21	20	20	12
	Phone	9	0.00	0.01	0.03	0.05	0.11	0.19	0.32	0.46	1	14	17	19	21	21	21	21
	Cellphone	10							0.00	0.02							1	20
IV.	Newspaper	11					0.31	0.30							21	20		
	Radio	12				0.13	0.28	0.38						18	21	21		
	TV	13					0.07	0.19	0.38	0.46					20	21	21	21
V.	PC	14							0.00	0.09							1	19
	Robot**	15								0.01								17
VI.	Rail – Freight	16	0.26	0.31	0.48	0.30	0.28	0.24	0.21	0.18	6	11	12	16	17	17	17	17
	Rail - Passengers	17	261	559	912	1005	1473	1524	1537	1730	7	11	11	13	16	16	17	16
	Truck**	18			0.41	1.91	2.58	2.64	2.99	3.5			9	17	21	21	21	21
	Car	19		.00	.01	.04	.10	.20	.30	.38		2	10	17	21	21	21	21
	Aviation - Freight**	20				22	270	885	1587	2397				2	21	20	21	21
	Aviation- Passengers	21			0	3	131	392	835	1360			1	18	21	21	21	21
VII.	Steam- and motorships	23+24	.26	.64	.88	.96	.99	1.00	1.00	1.00	14	15	14	15	13	13	11	9
VIII.	MWHr**	25		0.4	9.7	14.7	25..6	33.4	38.0	40.0		3	16	21	21	21	21	21

Notes: Real GDP measured in 1000 of 1998 US $, (*) units per 1000 persons, (**) units per $M of real GDP

Table 4. Speed of convergence, estimates of β

	Technological clusters								
	All	*I*	*II*	*III*	*IV*	*V*	*VI*	*VII*	*VIII*
Total	0.89								
	(0.00)								
Pre-1945	0.91	0.99	0.94	0.89	1.00		0.92	0.83	0.89
	(0.01)	(0.04)	(0.05)	(0.01)	(0.12)		(0.01)	(0.03)	(0.02)
Post-1945	0.87	0.90	0.86	0.85	0.78	0.92	0.90	0.32	0.93
	(0.01)	(0.08)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.04)	(0.01)

Notes: Standard errors are in parenthesis. The parameter β is defined as follows: $Y_{ijt}=\alpha+\beta Y_{ijt-1}+e_{ijt}$, where Y_{ijt} is the measure of technology adoption measure j *for country* i *at time* t*, and it is in logs whenever the variable is not a share.*
The speed of convergence is then given by -ln(β).

Table 5a. Variables used in panel data regressions

Dependent variables: logarithm of technology measures 7-21, and 25. Level of 2-6, and 23+24 from Table 1.

	Group	Abbreviation	Description	Source
A.	*Standard variables*	-	Technology-time dummies d_{jt}	-
		ln(RGDPpc)	logarithm of real GDP per capita	HCCTAD
B.	*Human capital endowments*	Prim.enr. 70-	Primary school enrollment rates before 1970	HCCTAD
		Prim enr. 70+	Primary school enrollment rates after 1970	World Bank (2000)
		Sec.enr. 70-	Secondary school enrollment rates before 1970	HCCTAD
		Sec.enr 70+	Secondary school enrollment rates after 1970	World Bank (2000)
		Prim.Att.	Primary attainment rate in population of age 25+	Barro and Lee (1994)
		Sec.Att	Secondary attainment rate in population of age 25+	Barro and Lee (1994)
		Tert.Att	Tertiary attainment rate in population of age 25+	Barro and Lee (1994)
C.	*Trade*	Openness	Exports + imports / GDP, nominal in 1000's US $	Calculated using HCCTAD
		Twt	trade weighted level of adoption of trading partners	HCCTAD, see equation ??
		TwtGDP	trade weighted GDP of trading partners	HCCTAD, see equation ??
D.	*Institutions*	Ex.mon.	Effective executive is monarch	HCCTAD
		Ex.pres.	Effective executive is president	HCCTAD
		Ex.prem.	Effective executive is premier	HCCTAD
		Ex.Other	Effective executive does not exist or does not hold formal government post.	HCCTAD
		Mil.Reg.	Dummy for (partially) military regime	Calculated using HCCTAD
		Legisla Eff	Index of legislative efficiency	Banks
		Party	Party legitimacy index	Banks
E.	*Technology interactions*	ln(MWHR)	Logarithm of 25. from Table 1.	HCCTAD
		ln(RailF)	Logarithm of 16. from Table 1.	HCCTAD
		ln(AviaF)	Logarithm of 20. from Table 1.	HCCTAD
		Prev.tech.	Logarithm of adoption level of previous technology*.	HCCTAD

Table 5b. Variables used in panel data regressions, Previous technologies

Group	Technology measure	Previous Technology
I.	Ring spindles	-
II.	Bessemer steel	-
	OHF steel	Bessemer steel
	BOF steel	OHF steel
	EAF steel	-
III.	Mail	-
	Telegrams	Mail
	Phone	Telegrams
	Cellphone	Phone
IV.	Newspaper	-
	Radio	Newspapers
	TV	Radio
V.	PC	-
	Robot	-
VI.	Rail – Freight	-
	Rail - Passengers	-
	Truck	Rail – Freight
	Car	Rail – Passengers
	Aviation – Freight	Truck
	Aviation- Passengers	Car
VII.	Steam- and motorships	-
VIII.	MWHr	-

Table 6. Pooled regressions

Dependent variables: technology measures 2-21,23+24, and 25 from Table 1.

Group	Variable	*6.1*	*6.2*	*6.3*	*6.4*	*6.5*	*6.6*	*6.7*	*6.8*	*6.9*
A.	*ln(RGDPpc)*	1.15 (0.03*)	1.12 (0.03*)	0.57 (0.07*)	1.10 (0.03*)	1.05 (0.04*)	0.93 (0.05*)	1.04 (0.35*)	1.04 (0.03*)	1.2 (0.09*)
B.	Prim.enr. 70-		0.09 (0.06)		0.06 (0.07)	0.08 (0.07)	1.23 (0.18*)	0.10 (0.07)	0.09 (0.07)	1.69 (0.26*)
	Prim enr. 70+		0.35 (0.21)		0.39 (0.23)	0.22 (0.23)	-0.11 (0.2)			-0.48 (0.4)
	Sec.enr. 70-		0.30 (0.08*)		0.36 (0.08*)	0.31 (0.08*)	0.37 (0.09*)	0.27 (0.08*)	0.3 (0.08*)	0.22 (0.12)
	Sec.enr 70+		0.08 (0.128)		0.05 (0.15)	-0.01 (0.15)	0.13 (0.27)			-0.36 (0.36)
	Prim.Att.			0.01 (0.00*)						
	Sec.Att			0.01 (0.00*)						
	Tert.Att			0.01 (0.00*)						
C.	Openness				0.06 (0.02*)	0.06 (0.02*)	0.24 (0.11)	0.07 (0.02*)	0.31 (0.09*)	0.35 (0.15*)
	Twt†									
	TwtGDP							-0.22 (0.06*)		
	Openness× TwtGDP								-0.15 (0.05*)	
D.	Ex.mon.					0.16 (0.07)		0.13 (0.07)	0.14 (0.07)	
	Ex.prem.					-0.11 (0.04)	0.06 (0.06)	-0.14 (0.04*)	-0.12 (0.04*)	-0.05 (0.08)
	Ex.Other					-0.33 (0.06*)	-0.17 (0.08)	-0.36 (0.06*)	-0.33 (0.06*)	-0.53 (0.11*)
	Mil.Reg.					-0.42 (0.08*)	-0.46 (0.15*)	-0.45 (0.08*)	-0.43 (0.08*)	-1.17 (0.19)
	Legislat. Eff.						-0.16 (0.05*)			-0.31 (0.07*)
	Party						0.08 (0.04)			0.75 (0.05)
E.	ln(MWHR)									0.06 (0.04*)
	Prev.tech†									0.16 (0.03*)
	No. of obs.	5488	5417	2341	4986	4986	2118	5057	5057	1000
	R^2 *(within)*	0.24	0.24	0.17	0.23	0.25	0.33	0.25	0.24	0.48

Notes: ***Standard errors in parenthesis.*** *(*) denotes significance at 1% level, (†) denotes instrumented for with 5 year lagged values.*

Table 7a. Technology specific regressions

Dependent variables: technology measures 2-21,23+24, and 25 from Table 1.				
Group	Variable Dependent variable	*7.1* *Whole sample.*	*7.2* *Technologies with previous technologies.*	*7.3* *Technologies without previous technologies.*
A.	*ln(RGDPpc)*	0.91 (0.06*)	1.35 (0.08*)	0.58 (0.18*)
B.	Prim.enr. 70-	1.26 (0.19*)	1.92 (0.26*)	0.8 (0.26*)
	Prim enr. 70+	0.11 (0.31)	-0.44 (0.41)	0.83 (0.46)
	Sec.enr. 70-	0.28 (0.09*)	0.26 (0.13)	0.26 (0.13)
	Sec.enr 70+	0.07 (0.28)	-0.25 (0.36)	0.57 (0.41)
C.	Openness	0.11 (0.11)	0.34 (0.15)	-0.22 (0.16)
D.	Ex.mon.			
	Ex.prem.	0.04 (0.06)	-0.062 (0.08)	0.21 (0.08)
	Ex.Other	-0.19 (0.08)	-0.6 (0.11*)	0.3 (0.12)
	Mil.Reg.	-0.48 (0.16*)	-0.73 (0.22)	-0.22 (0.22)
	Legislati Eff	-0.14 (0.05*)	-0.34 (0.07*)	0.003 (0.06)
	Party	0.06 (0.04*)	0.1 (0.05)	0.04 (0.05)
E.	ln(MWHR)	0.11 (0.03*)	0.08 (0.04)	0.16 (0.04*)
	No. of obs.	1978	1000	978
	R^2 *(within)*	0.34	0.47	0.26

Notes: ***Standard errors in parenthesis.*** *(*) denotes significance at 1% level, (†) denotes instrumented for with 5 year lagged values.*

Table 7b. Technology specific regressions

Group	Variable	*7.1*	*7.2*	*7.3*	*7.4*	*7.5*	*7.6*	*7.7*	*7.8*	*7.9*
	Dependent variable	*I.*	*II.*	*III.*	*IV.*	*V.*	*14*	*VI.*	*VII.*	*VIII.*
A.	*ln(RGDPpc)*	1.02	0.25	1.62	1.15	1.80	1.35	1.59	0.03	0.40
		(0.23*)	(0.07*)	(0.18*)	(0.13)	(0.53*)	(0.45*)	(0.1*)	(0.02)	(0.11*)
B.	Prim.enr. 70-	-0.03	-0.69	0.17	0.59			1.06	0.07	0.57
		(0.56)	(0.17*)	(0.27)	(0.41)			(0.24*)	(0.04)	(0.26)
	Prim enr. 70+				0.12	0.89		0.83	-0.02	-0.57
					(0.67)	(1.61)		(0.54)	(0.18)	(0.85)
	Sec.enr. 70-	-0.64	0.17	0.39	0.54			-0.26	0.05	0.95
		(0.35)	(0.1)	(0.3)	(0.21*)			(0.18)	(0.05)	(0.29*)
	Sec.enr 70+				0.26	-0.11		-1.02	-0.03	0.03
					(0.58)	(0.82)		(0.37*)	(0.13)	(0.58)
	Prim.Att.									
	Sec.Att									
	Tert.Att						0.03			
							(0.01*)			
C.	Openness	0.76	0.05	0.16	-0.38	-0.00	0.55	0.21	0.04	0.78
		(0.35)	(0.05)	(0.16)	(0.22)	(0.34)	(0.3)	(0.12)	(0.03)	(0.18*)
	Twt†									
	TwtGDP			0.21						
				(0.21)						
	Openness× TwtGDP									
D.	Ex.mon.									
	Ex.prem.									
	Ex.Other	0.14	-0.47		-0.41			-0.66	0.25	0.36
		(0.54)	(0.07)		(0.15*)			(0.12*)	(0.06*)	(0.17)
	Mil.Reg.									
E.	ln(MWHR)	-0.19	-0.15	0.45	0.17	0.26	0.24	0.11	-0.01	
		(0.11)	(0.02*)	(0.06*)	(0.07)	(0.17)	(0.19)	(0.04*)	(0.01)	
	ln(RailF)		0.04	0.03						
			(0.01*)	(0.04)						
	Prev.tech.†		-0.40	-0.15	0.25			0.12		
			(0.06*)	(0.12)	(0.09*)			(0.03*)		
	No. of obs.	53	600	327	226	104	28	947	220	349
	R^2 (within)	0.4	0.29	0.47	0.67	0.17	0.7	0.42	0.1	0.22

Notes: ***Standard errors in parenthesis.*** *(*) denotes significance at 1% level, (†) denotes instrumented for with 5 year lagged values.*

Table 8. Pre- and post-1945 regressions

Group	Dependent variable	*8.1* *whole sample*	*8.2* *Pre-'45*	*8.3* *post-'45*
A.	*ln(RGDPpc)*	1.04 (0.04*)	1.11 (0.07*)	0.91 (0.07*)
B.	Prim.enr. 70-	0.4 (0.1*)	0.2 (0.12)	1.17 (0.21*)
	Prim enr. 70+	0.22 (0.33)		0.17 (0.32)
	Sec.enr. 70-	0.19 (0.09)	-0.13 (0.24)	0.33 (0.1*)
	Sec.enr 70+	-0.19 (0.28)		0.15 (0.28)
C.	Openness	0.03 (0.08*)	-0.02 (0.12)	0.12 (0.11)
D.	Ex.mon.	0.41 (0.15*)	-0.27 (0.17)	
	Ex.prem.	-0.06 (0.05)	-0.27 (0.1*)	0.10 (0.055)
	Ex.Other	-0.4 (0.07*)	-0.76 (0.13*)	-0.1 (0.08)
	Mil.Reg.	-0.33 (0.09*)	-0.35 (0.13*)	-0.31 (0.15)
	Legisla Eff	-0.00 (0.02)	0.03 (0.03)	-0.08 (0.04)
E.	ln(MWHR)	0.15 (0.02*)	0.18 (0.028)	0.12 (0.03*)
	No. of obs.	2974	1225	1749
	R^2 *(within)*	0.35	0.41	0.31

Notes: ***Standard errors in parenthesis.*** *(*) denotes significance at 1% level.*

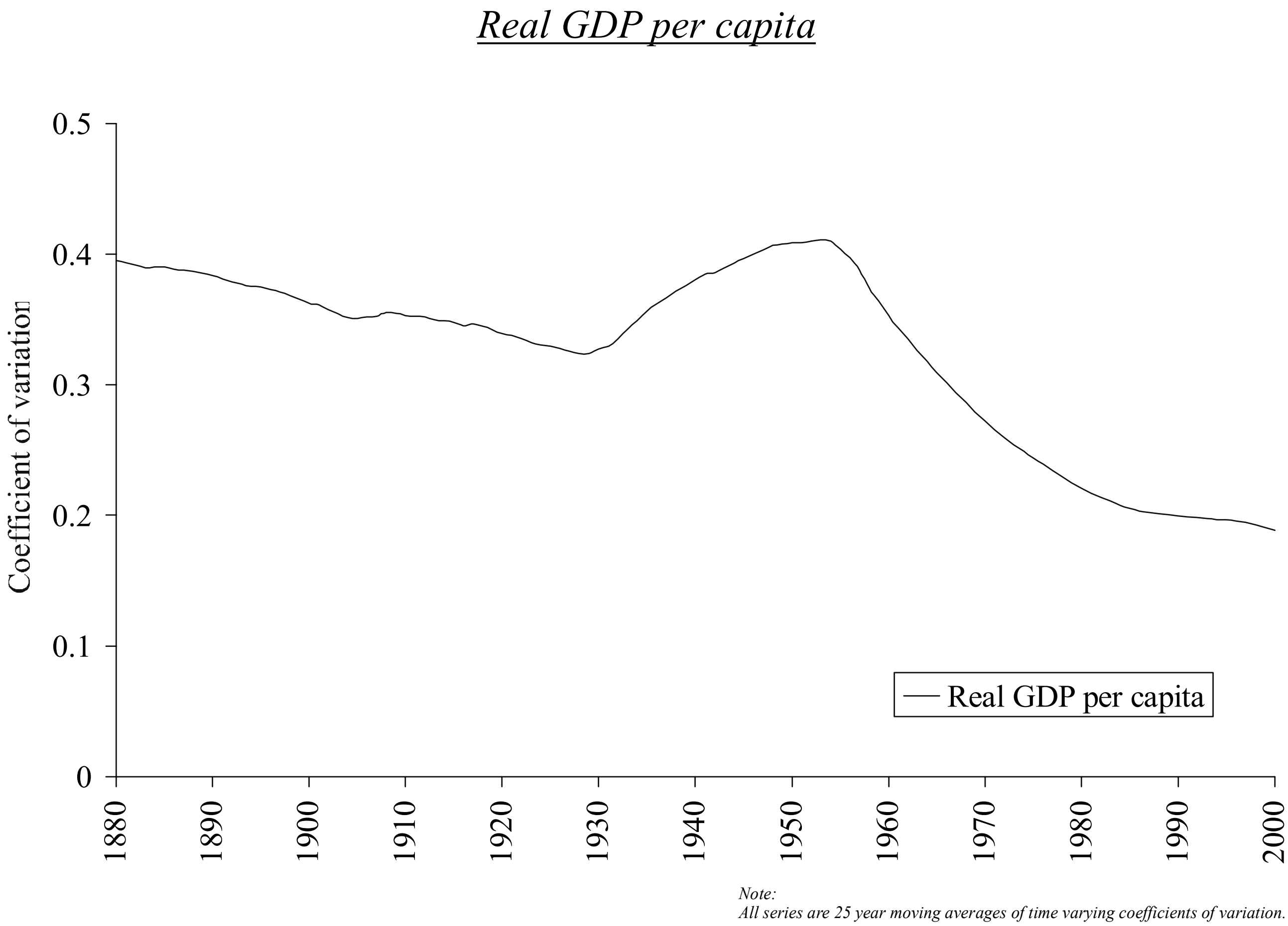
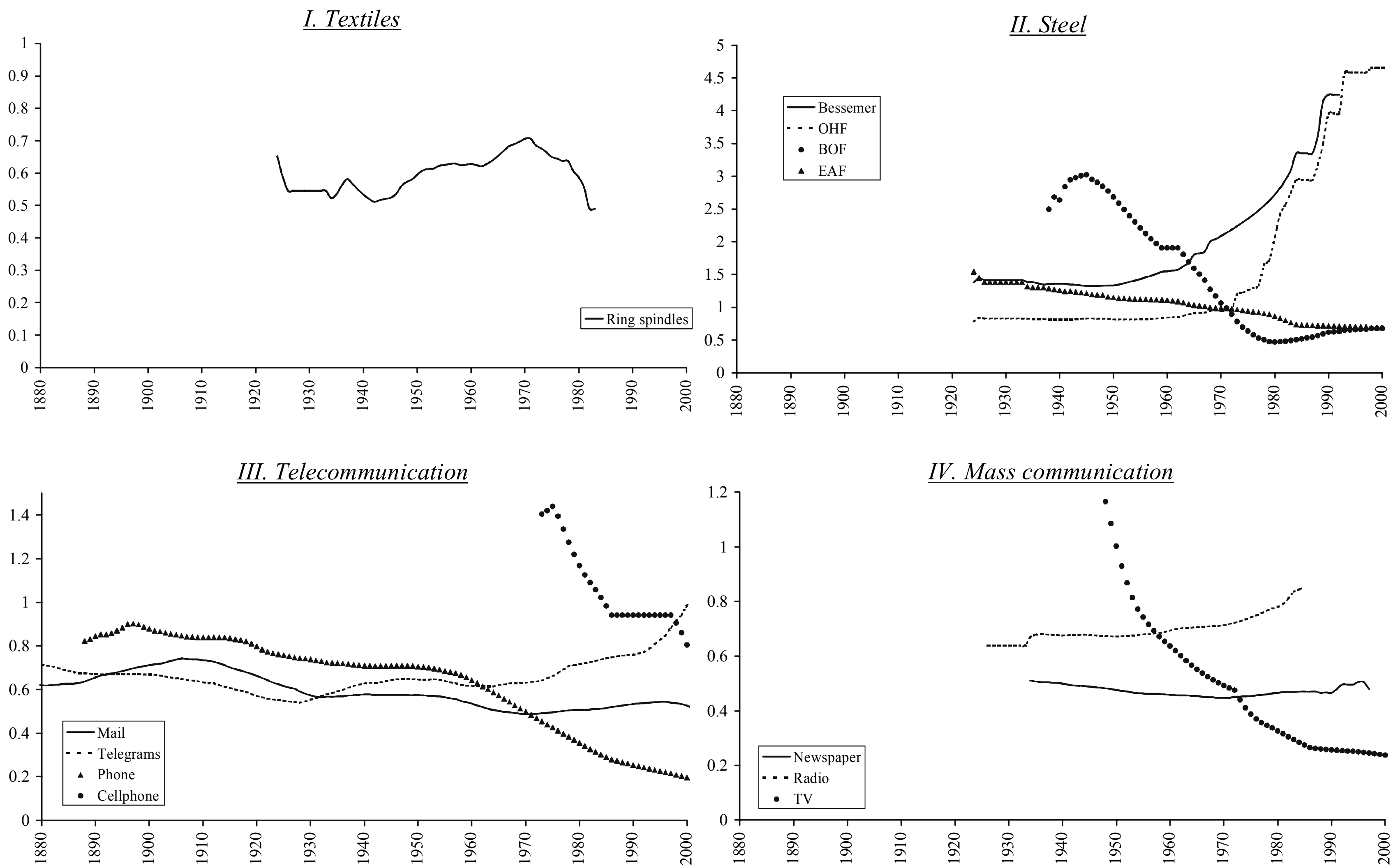
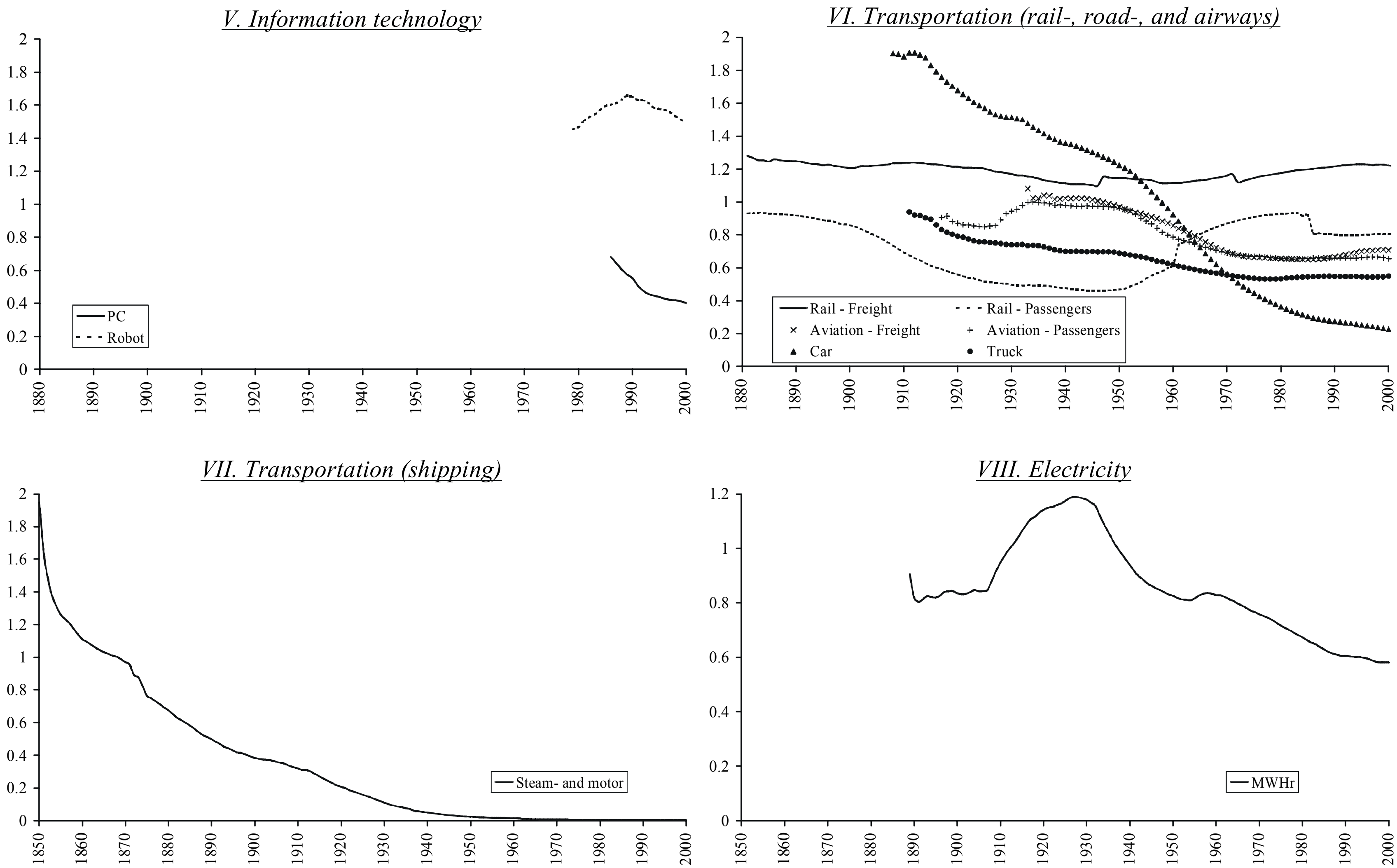


Figure 1. Evolution of coefficient of variation for real GDP per capita



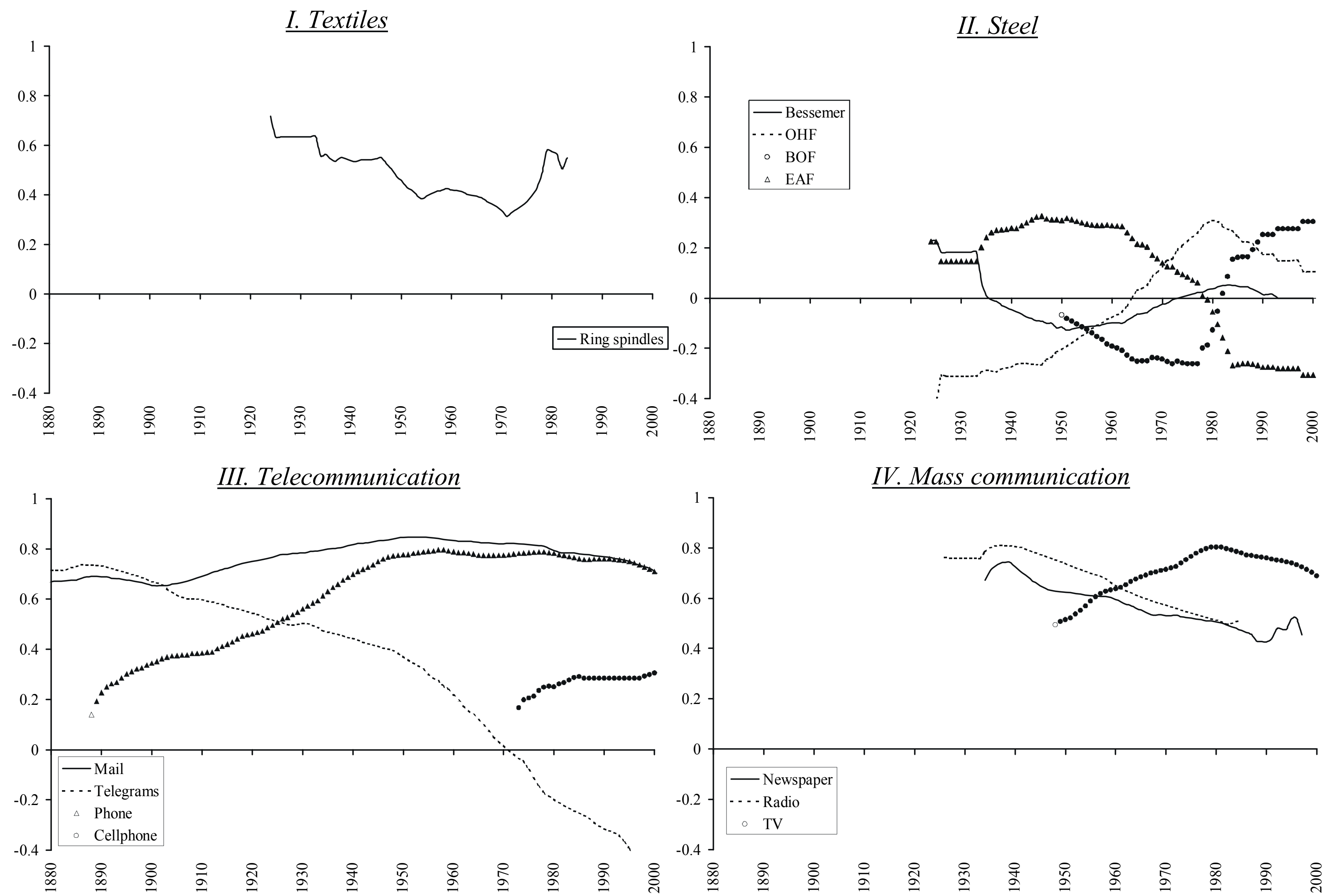
Note:
All series are 25 year moving averages (5 year moving averages for V) of time varying coefficients of variation. The coefficients are only calculated if the sample size is bigger than or equal to 10 (5 for electricity).

Figure 2a. Descriptive statistics – coefficients of variation



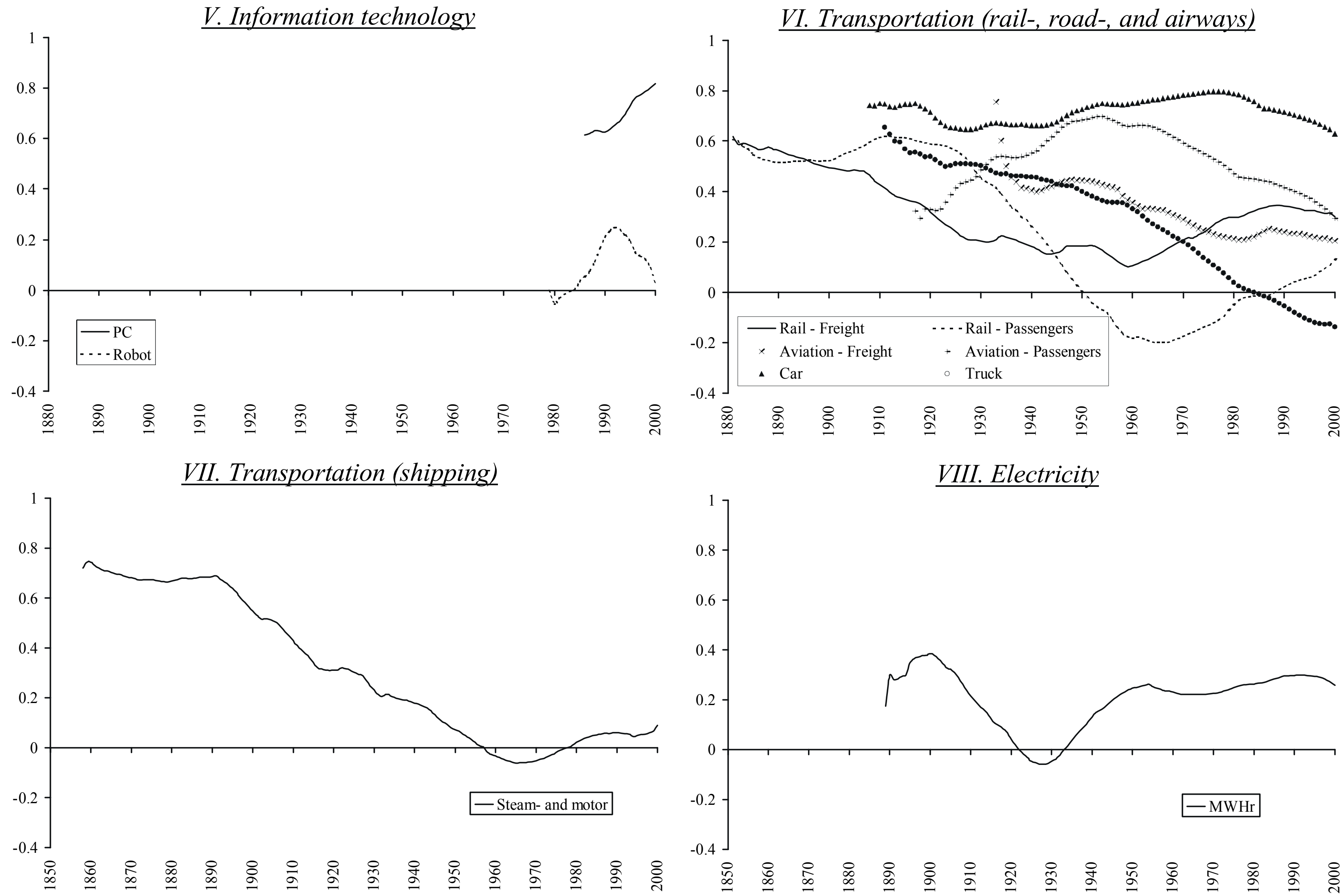
Note:
All series are 25 year moving averages (5 year moving averages for V) of time varying coefficients of variation. The coefficients are only calculated if the sample size is bigger than or equal to 10 (5 for electricity).

Figure 2b. Descriptive statistics – coefficients of variation



Note:
All series are 25 year moving averages (5 year moving averages for V) of time varying correlations with log real GDP per capita. The correlations are only calculated if the sample size is bigger than or equal to 10 (5 for electricity).

Figure 3a. Descriptive statistics – correlations with real GDP per capita



Note:
All series are 25 year moving averages (5 year moving averages for V) of time varying correlations with log real GDP per capita. The correlations are only calculated if the sample size is bigger than or equal to 10 (5 for electricity).

Figure 3b. Descriptive statistics – correlations with real GDP per capita

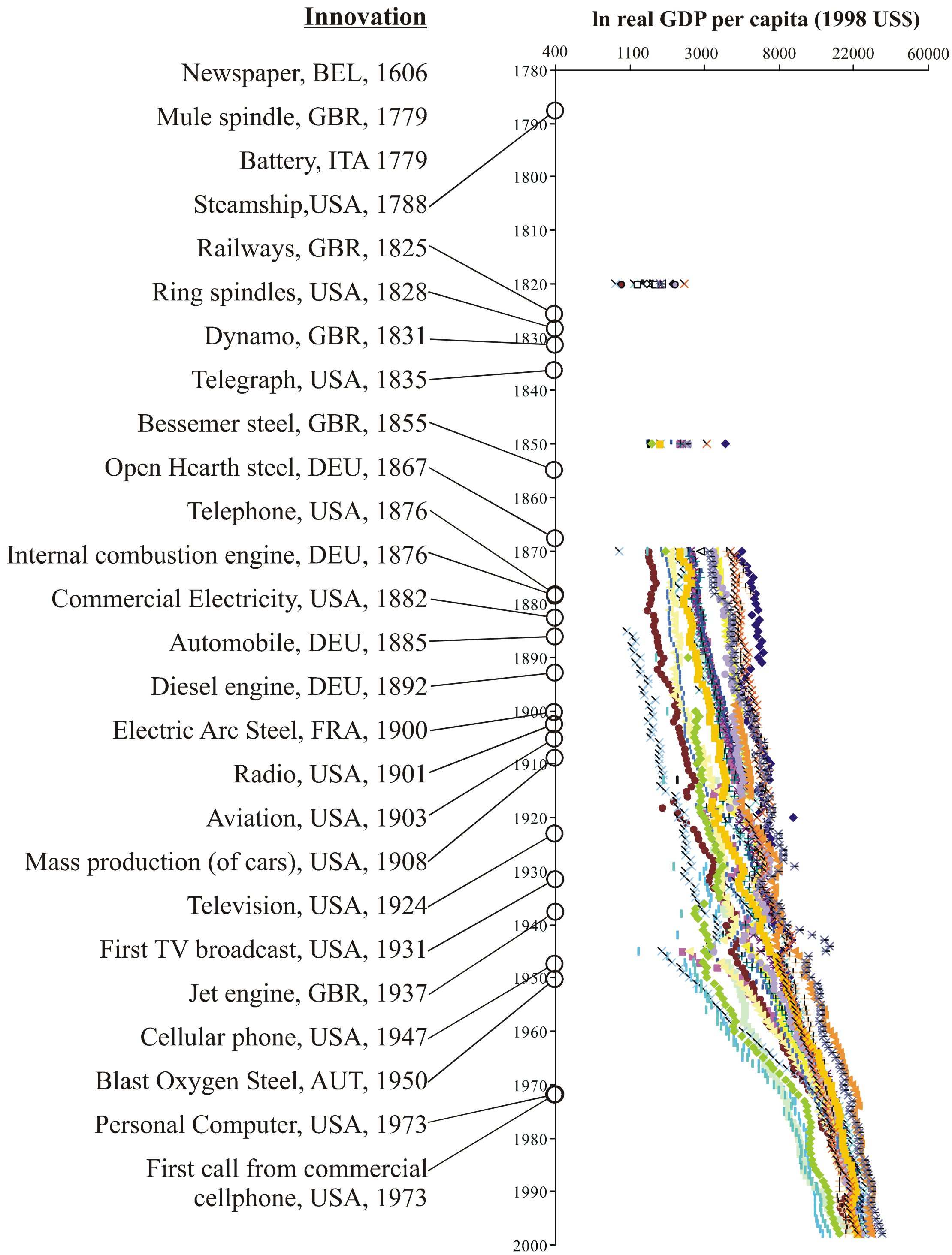
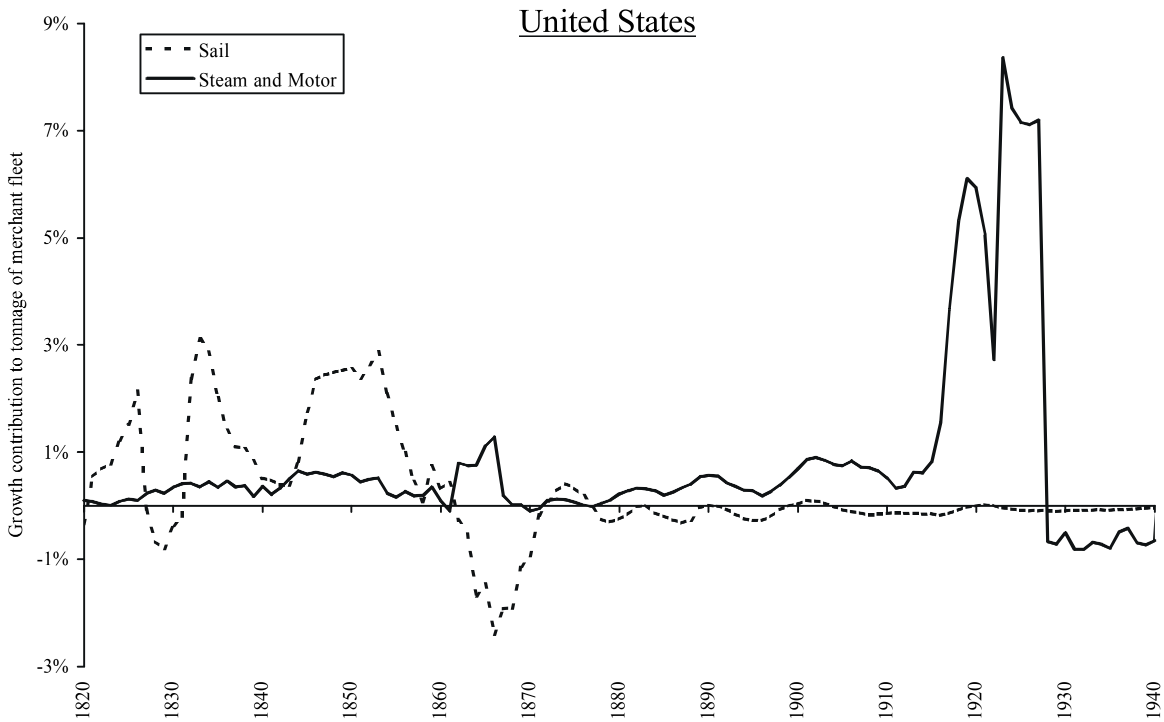


Figure 4. Major innovations covered by our data



Note: All series are 5 year moving averages

Figure 5. Locking – the United States merchant fleet

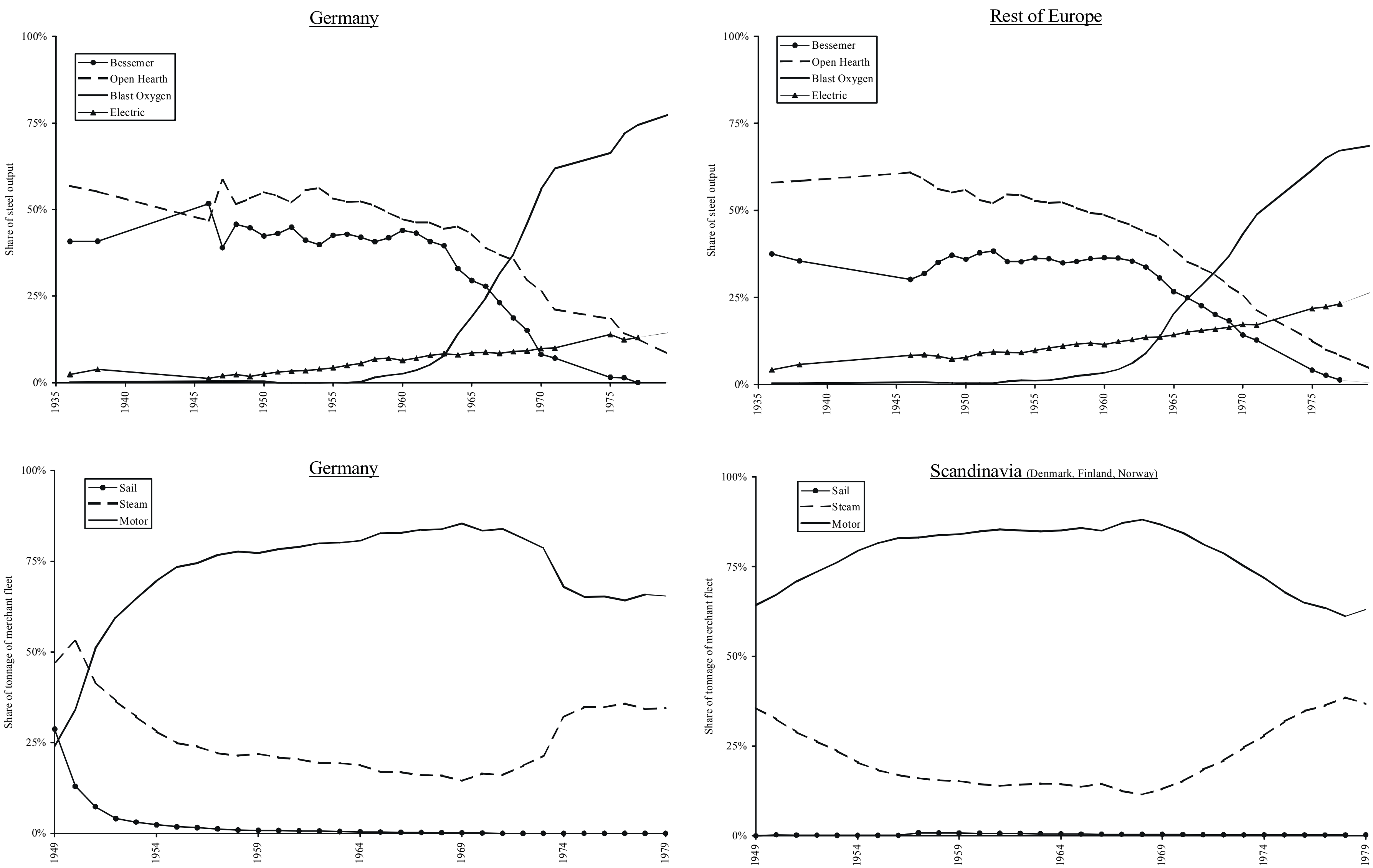


Figure 6. Postwar vintage shares for Germany and counterparts